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Three Essays on Health, Health Systems, And Migration

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Three Essays on Health, Health Systems, And Migration

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by

Joseph Chidinma Nwadiuko

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ABSTRACT OF THE DISSERATION

Three Essays on Health, Health Systems, And Migration

by

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Doctor of Philosophy in Health Policy and Management
University of California, Los Angeles, 2024
Professor Arturo Vargas Bustamante, Chair

Immigration is a debated topic in the US and the high-income world. One consequence of widespread negative perceptions of immigrants are legal crackdowns on immigrants themselves, which can lead to incarceration and occupational exclusion, and can affect already excluded racial groups (such as Black individuals). This dissertation is a collection of three essays that attempts to disentangle the assumptions behind these interventions as well as their consequences on marginalized persons.

The first paper posits immigration enforcement within the larger context of mass incarceration in the United States, which has provided employment to rural distressed communities, leading them to compete for immigration and criminal justice prisons. The paper looks at the beginning of the COVID pandemic (2020-2022) to determine whether there were negative externalities to rural hospitals adjacent to carceral facilities, in the form of strained hospital units or worsened operating margins. It finds that rural hospitals geographically adjacent to carceral institutions in minority-majority communities have an 31% increased probability of having completely full

ICUs, with no impact in majority-majority communities and no operating margins difference with controls.

The second paper examines the relationship between GDP and physician emigration, using the framework of the mobility transition, which would predict a monotonous decline in emigration with origin country GDP for highly educated professionals like physicians. Using OECD physician entry data from 2000-2019 it is found that the relationship between GDP per capita is heterogenous by geographic region, with a negative relationship in most regions except for sub-Saharan Africa (where there is no relationship), the Middle East and North Africa (where the relationship is quadratic) European countries outside the European Union (where the relationship is positive).

The third paper looks at the intersection of racism and legal exclusion through the lens of Black undocumented immigrants. Using 1999-2018 National Health Interview Survey data, the paper examines how 1) among Black individuals, immigrant status correlate and 2) among undocumented immigrants, race and ethnicity correlate to 5 measures: health insurance coverage, physician utilization, hospitalizations, mental distress, and sleep. Results show that legal status, race, and ethnicity are all important measures of healthcare access and mental health.

The dissertation of Joseph Nwadiuko is approved.

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2024

DEDICATION

To my ancestors, brothers, and sisters who made it across the seas,
for those left behind
and for those in between.

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Introduction

Immigration is an important component of all human societies since the beginning of time; moreover, the percentage of the world's population that has immigrated has remained flat at around 2-3% since 1960, with rates for refugees hovering around 0.1%-0.3% since 1951[1,2]. However, immigration has become increasingly contested by a variety of forces. Over the past 10 years there have been an increase in the rhetoric against immigrants in the United States and Europe, leading to several policies that have restricted international movement. These restrictive policies have entailed an increase in enforcement efforts (with associated public health risks) towards immigrants, with the aim of reducing mobility across the skill spectrum. However, the impacts of these restrictions on immigrants and spillover effects on local communities do not receive much consideration. Furthermore, policies might ignore the economic drivers of emigration from origin countries. These drivers, significantly, might be more important in driving immigration than policies in recipient nations[3].

The theme of this dissertation is to understand the realities that influence migration and the impact of host countries' reaction to immigration, with a focus on health systems. The dissertation will be composed of three papers with three areas of focus: the spillover impacts of immigration detention and incarceration; the economic drivers of physician migration, and the intersectional impact of anti-immigrant and anti-Black racism on health outcomes and health access (including insurance coverage) on undocumented Black immigrants. The impetus behind the three papers will be described below.

The Financial and Capacity Impacts of Carceral Institution Adjacency on Rural Hospitals during the COVID Pandemic

Immigration detention has a long complex history in the United States with a resurgence since the 1980s tied to trends in mass incarcerations during the same period. Criminal Justice facilities (prisons and jails) and immigration detention facilities have a deeply symbiotic relationship; 76% of immigration detention detainees held in 170 local jails that are rented out in part or full to the Department of Homeland Security[4].

The beneficiaries of incarceration of immigrants and nonimmigrants are also the same. The five major prison corporations operate 24% of correctional facilities and own facilities that hold 81% of all immigration detainees[5]. Another, more hidden, set of beneficiaries are hosting towns, which might receive rental income and other economic benefits from hosting carceral institutions. The town of Adelanto, CA for example, receives $1 million a year—ten percent of its operating budget—from the GEO group to operate the ICE Adelanto Detention Center on city property[6]. This is beyond the employment offered to residents in often impoverished rural communities.

These beneficiaries play an important part in keeping carceral institutions alive, often by switching to immigration detention models. As an example, Louisiana underwent prison reform in 2017, leading to the decline of its incarcerated population by 24% from 2017-2022 and the closure of 3 state prisons and many local jails. Between 2018 and 2019, ICE opened 8 new facilities in closed jails and prisons in Louisiana, paying double what the state paid to house detainees[7,8]. (The reverse has occurred: Orange County, CA canceled its contract with ICE in 2019 in response to activism but expanded its capacity to detain more people with mental health conditions one year later using ICE occupied beds). This phenomenon has been labeled the "Carceral Carousel" by some groups[9].

However, while some local benefits of housing detainees are clear, there might be some unexplored negative externalities. Several quasi-experimental studies, for example, have concluded that the overall economic impacts of hosting a carceral institution might be null aside from direct employment impacts[10–13]. During the COVID pandemic, another set of risks became clear, as infections from carceral institutions spilled over into communities, as seen in the city of Chicago and Marion County, OH[14,15] . Rural communities are significantly vulnerable, as local governments might depend on prison income but do not have health systems that can withstand the capacity and financial implications of a surge. Communities near immigration detention facilities are also particularly at risk due to poor implementation of hygiene and social standards as well as ICE's practice of rapidly transferring detainees across during the pandemic, with one analysis demonstrating at least 676 transfers between 2020 and 2021[16].

There is yet no published research quantifying the impact of peri-pandemic risks of carceral institutions on rural communities, and whether immigration detention facilities might raise that risk. The analysis proposed uses hospital capacity data and financial data from the Department and Health and Human Services to determine whether any hospital within proximity of any carceral institution is a higher risk of capacity strain or financial losses, and whether immigration detention facilities are a higher risk for either outcome compared to other facilities.

The Mobility Transition: Economic Determinants of Physician Emigration

It is not just immigrant flows across the Southern Border that have become politicized. Even the flow of high-skilled immigrants has become contested, albeit for different reasons. Global health advocates have been concerned that the outflow of health workers from poor countries might have deleterious effects on the health systems of those countries. As one example, in the past 10 years there have been editorials in the New York Times, Guardian, Los Angeles Times and Scientific American describing the United States explicitly as "stealing" the world's doctors, unfortunately occluding the personal agency that health workers choose to make to live outside their home country[17–20]. This rhetoric has led to greater reliance on international regulations to restrict recruitment of physicians from the world's poorest countries, as encouraged by the World Health Organizations Global Code of Practice on this International Recruitment of Health Personnel [21].

On the other hand, there is relatively little policy attention to the economic/structural forces that might drive these decisions to relocate and there is little focus on whether those same forces affect the migration of richer physicians. Various models have attempted to describe these models to better predict the flow of emigrants across professions. One major economic model, the mobility transition, has held that emigration flows are tightly correlated with GDP per capita. Overall migration (across professions) increases within low-income nations as their GDPs increase up until countries reach a GDP per capita of $6,000, after which migration falls. Analyses have reproduced this phenomenon across all countries using data from 1950 to the present,[22]. Theoretically, this is a phenomenon driven by emigrants individually becoming wealthier as their nations develop, often before state capacity evolves to accommodate its development. Emigrants with resources might initially choose to leave until conditions favor them staying. Among highly educated (i.e., college educated) professionals, migration rates monotonously decline with GDP per capita[23]. However, physicians, on average, might have more resources than the surrounding population even in low-income nations, leading them to leave more readily than the local population.

Examining the mobility transition model for physicians might help better predict emigration flows from countries, allowing them to better predict future staffing levels. It also will inform the discussion on physician emigration, potentially providing an upstream target—source country economic development—to decrease emigration without relying on restrictions. The analysis proposed will examine physician emigration data from 2000-2019 to OECD destination nations to determine the correlation between emigration and source country GDP per capita.

Health Outcomes among Black Undocumented Immigrants

Anti-Black racism has been a perverse force within the United States since the foundation of this country. As the number of policies rise against undocumented immigrants in the United States, Black immigrants might be particularly vulnerable due to increased enforcement, compared to other undocumented immigrants. On the other hand, because of the lack of intergenerational exposure to American slavery and racial stratification, they may have relatively better outcomes than US-born Black American, although exposure to such racism in the US over time might attenuate that difference.

However, there is little written about the welfare of Black undocumented immigrants in the United States. A literature review has found only 4 articles written on the topic, by two authors. The first three articles, authored by Oluwatoyin Olukotun, demonstrate that undocumented Black patients have significant fear-based and financial barriers to care and as a result lack regular access to primary care and delay acute care seeking; once they arrive to health care, they receive insensitivity from providers and mistrust staff; and they are often isolated and financially vulnerable, with resultant stressors buttressed by faith-based coping mechanisms.[24–26] The other article, by Jonathan Ross, details how stigma related to immigration and HIV status might impede access for undocumented African immigrants living with HIV in New York City. However, once connected to care, they have positive relationships with their care providers.[27]

Research on outcomes of Black immigrants in the United States holds that they tend to have better self-reported health than Black natives, a trend that holds for all immigrants compared to natives and which is termed the "immigrant health paradox"; this trend also holds for birth outcomes, mortality rates, self-reported hypertension, diabetes and obesity outcomes [28,29] (Further discussion of this is reported in the Conceptual Model). However, that research does not focus on undocumented immigrants, who experience vulnerability at the nexus of immigration status, race, ethnicity, and class. Legal exclusion from health insurance coverage (e.g. Medicaid in most US states), labor market exclusion, and susceptibility to deportation regimes overlap, exacerbating inequities in health and healthcare access in this population.

There are several models that guide what outcomes might be at risk. Health utilization might be reduced due to decreased health system trust; exposure to anti-Blackness and liminal legal status might increase risk of severe mental distress and sleep disturbances. This study uses data from the National Health Interview Survey (NHIS) from 1997-2018 to determine Black undocumented immigrants' relative risk of these conditions compared to White non-Hispanic citizens as well as trended risk over time spent in US. Two categories of models will be used: one with an indicator for Black indicators across race, and the other with a measure identifying undocumented immigrants across race. Undocumented immigrants will be identified using the residual method, which has been used in other literature to identify this population.

Chapter 1: The Financial and Capacity Impacts of Carceral Institution Adjacency on Rural Hospitals during the COVID Pandemic

Introduction: A relatively unexplored beneficiary of carceral proliferation is rural towns, which often depend on prisons for economic development. However, it is known that COVID infections might spillover from carceral institutions (CI) into local communities. Furthermore, rural hospitals have been financially challenged, which might hinder their capacity to handle high patient caseloads. This might be particularly true in rural Black, Latino, or Native-majority ("minority-majority") communities which have suffered underinvestment due to structural racism. The purpose of this study is to examine whether rural hospital proximity to a carceral institution is associated with increased intensive care and floor strain and lower operating margins during 2020-2022.

Methods: Using data from the UCLA COVID Behind Bars Database and the Health and Human Services COVID-19 Reported Patient Impact and Hospital Capacity Dataset, we mapped out the three closest rural hospitals by driving distance to every jail, state prison, immigration detention facility and juvenile detention facility in the United States. Hospital rurality was determined by location in a census tract determined by Health Resources and Service Administration to be rural. We then identified differences in 100% ICU (primary outcome) and floor capacity rates between proximal and non-proximal hospitals between June 2020 and January 2022, reflecting data availability. Using Medicare Hospital Cost Reports, we analyzed difference-in-differences of operating margins for proximal and non-proximal hospitals before and after the 2020 fiscal year. For strain data, we controlled for 2020 census tract-level social vulnerability indices (SVI), county-wide vaccination rates, and countywide ICU or floor beds per capita; for operating margins we controlled for SVI and critical access hospital status. We interacted the ordinal distance with minority-majority community status (i.e, majority Black, Latino, Native American population in 2020 census tract estimates), using an OLS regression with interacted county and month

fixed effects for strain and interacted county-year fixed effects for operating margins. We also employed Geographic Weighted Regression to identify spatial clustering of highest effects.

Results: We identified 1,687 carceral institutions and 2,184 rural hospitals, of which 29% were the closest, 20% the 2nd closest, and 14% the third closest to CIs'. Rural hospital ICUs on average were at capacity 1.1% of all hospital weeks and general wards 0.4% of all hospital weeks. On average there was no statistical significance of proximity on rural or ICU strain, but for minority majority communities there was a 31.2% (95% CI 6.35%, 56.0%) absolute increase in ICU strain for immediately proximal rural hospitals in minority-majority and 0.4% (95% 0.01, 0.89%) absolute increase in floor strain in 2nd closest hospitals. Rural hospitals had an average operating margin of -6.1%, with no difference between CI-proximal and non-proximal rural hospitals in interacted and non-interacted models. GWR modeling showed ICU strain greatest impact in the lower Mississippi Valley.

Conclusions: During the beginning of the pandemic, CI-proximal rural hospitals in minority-majority community were susceptible to ICU strain, which could potentially increase patient mortality, with no difference in floor strain or operating margins.

Introduction

Hospital capacity strain is a recurrent concern since the beginning of the COVID pandemic. Aside from the news-grabbing pictures of beds lining hospital hallways, studies have also shown that patient harm can result from overcrowding: intensive care unit bed use at 75% capacity nationwide during the pandemic was projected to be associated with 12,000 excess deaths 2 weeks later [30].

Rural hospitals are particularly under-resourced and vulnerable to outbreaks that may overwhelm their financial and physical capacity, such as the COVID pandemic. While they might have lower occupancy rates than urban hospitals, they also have less staff capacity, which is critical for intensive unit care operations and other patient care roles.[31–33] Furthermore, they have lower financial reserves, leading to at least 21 rural hospitals closing since the beginning of the pandemic, with an additional 450 hospitals identified as being at risk of closure[34]. Rural hospitals in counties with higher proportions of Black, Hispanic, and Native American residents had a higher risk of closure[35]. As part of the CARES act, the Biden administration distributed $175 billion of subsidies based on hospital-reported expected losses of revenue. While rural hospitals ended FY2020 with an average profit margin of 7.5%, this was supported heavily by subsidies against an operating margin of -14%[36]. Furthermore, the CARES act funding ran out in early 2022, leaving hospitals vulnerable to further financial shocks, a concern as 53% are projected to have negative margins through 2022 due to increasing labor supply costs[37].

Carceral institutions were hotspots of SARS-CoV-2 transmission during the pandemic, with infection and mortality rates often surpassing that of local populations[38]. While these facilities can have infections introduced to them from countywide spread, due to either prisoner turnover or employee contact, those infections can also spill over to local populations. A series of reports from the Prison Policy Initiative suggest that counties with prisons had earlier arrival of outbreaks and had faster spread, with prisons and jails being linked to 566,804 additional COVID-19 cases during Summer of 2020[15]. One case of this was in Illinois where for each arrested individual cycled through Cook County Jail, five additional cases sprouted in the former inmate's ZIP Code[14]. Another case is the more rural Marion County, Ohio, which had the second highest infection rate in the United States during April of 2020, largely driven by an outbreak at the Marion Correctional Institute.[15]

Many carceral institutions (CIs) are in rural regions where their local hospitals are uniquely vulnerable to capacity strain. For example, a 2020 study showed that one-third of jail detainees in Mississippi, Montana, North Dakota, and West Virginia were in counties with no ICU beds[39]. This historically was due to perceived promises of job creation during the prison construction boom of the late 1900s, although studies suggest that prison construction did not lead to economic growth[40–42]. In this analysis, we will attempt to identify the causal impact of having a carceral institution within a rural hospital's vicinity on hospital capacity strain and financial losses during the pandemic. My hypothesis, guided by the conceptual model below, assumes that rural hospitals in the vicinity of a CI will be more likely to have strain and likely to suffer more financial losses during the pandemic.

Conceptual Model

The conceptual models described below are distilled in Figures 1 and 2. There are three primary pathways of COVID impact from carceral institutions into hospital strain: one is direct, and the other two are indirect. The first (direct) pathway involves direct prisoner transfer into local hospitals. In many cases, carceral institutions have preferred hospitals that inmates are transferred to, which may become full in the case of CI-driven outbreaks. (It is theoretically possible, however, that those hospitals were under capacity strain during the pandemic, forcing emergency medical services and CI officials to choose alternate sites of hospitalizations.) The second pathway involves staff turnover, which may be responsible bi-directionally for introducing infections into the CI and carrying it into the community[43,44] . The final mechanism is unique to jails and involves turnover of prisoners in and out of local communities, as seen in the Cook County Jail.

The turnover in a carceral population might also influence infection dynamics in and out of the facility. Jails and immigration detention facilities have relatively high rates of turnover, either due to short institutional stays (as referenced above) or to high inter-facility transfer (in the case of immigration detention facilities in particular)[16]. As such, these facilities might have differing risk profiles for spillover.

The likelihood of community outbreak (as shown in Figure 1) is modified by local vaccination rates, local adherence to nonpharmaceutical interventions (e.g., masking, avoiding large gatherings), and socio-economically driven exposure to COVID. The former two measures are likely influenced by political affiliation, with several studies linking mobility and social distancing adherence to political affiliation.[45–47]

Rural hospitals across the nation face staffing shortages and financial strains that made them vulnerable during the pandemic, but this pressure is acute within states that have not expanded Medicaid (with said states accounting for 74% of all rural hospital closures between 2010 and 2021). [48] Several national and regional trends affect these facilities: first, elective patient volumes, which are already low (with an average pre-COVID occupancy rate of 35% compared to 65% in urban facilities), might have fallen further during the pandemic, as patients might have been more afraid to visit hospitals or were denied elective procedures if being at capacity made it challenging to admit patients afterwards. Furthermore, labor, drug and personal protective equipment costs have increased during the same period. Finally, the economic costs during the pandemic might have manifested by decreased insurance coverage, leading to greater dependence on Medicaid and charity care and more strained hospital balance sheets[48] . In California between 2020-2021, there was an estimated $3 billion loss by safety net hospitals between and the California Health Association estimated a statewide loss of $12 billion after pandemic assistance, driven partially by declines in outpatient volume and procedures (particularly during the shutdown period), but particularly by increases in costs of traveling labor and supply chain failures[49,50]

Since rural hospitals are already tenuously situated financially and capacity wise, they can easily be overwhelmed by a CI mediated surge in infections (Figure 2). Rural hospitals in southern states, which both have not expanded Medicaid and participated in the prison construction boom of the late 20th century, might be particularly vulnerable. Facilities that are heavily utilized by CI's for both elective and emergency hospitalizations might have neutral or positive financial benefits, but it is possible that those hospitals and the ones outside of CI's referral networks might suffer negative financial effects from COVID-related financial losses, particularly due to COVID-related admissions "crowding out" beds for elective, more financially beneficial admissions. Finally, economic and livability standards might decline in the communities around CI's, causing the labor pool to decline and forcing facilities to become more reliant on more expensive temporary labor contracts for staffing. All these factors might lead to CI adjacent facilities to differentially lose operating revenue. However, it is possible that the reverse might happen; that is, prisons closest to hospitals might provide clinical revenue that might offset labor supply costs, providing relative financial protection to other rural hospitals.

These realities are distilled in Figures 1.1 and 1.2. In Figure 1.1, community poverty might drive the decision to have a CI sited. CI COVID infections can penetrate the community, and the reverse. The severity of CI COVID infections might be moderated by prison level vaccinations and social distancing measures. The same goes for community spread; while states might provide regulations and resources to support social distancing and vaccinations, the uptake of those measures will depend on the local regulations and behavior patterns.

Figure 1. 1 Conceptual Model for Rural Hospital Strain

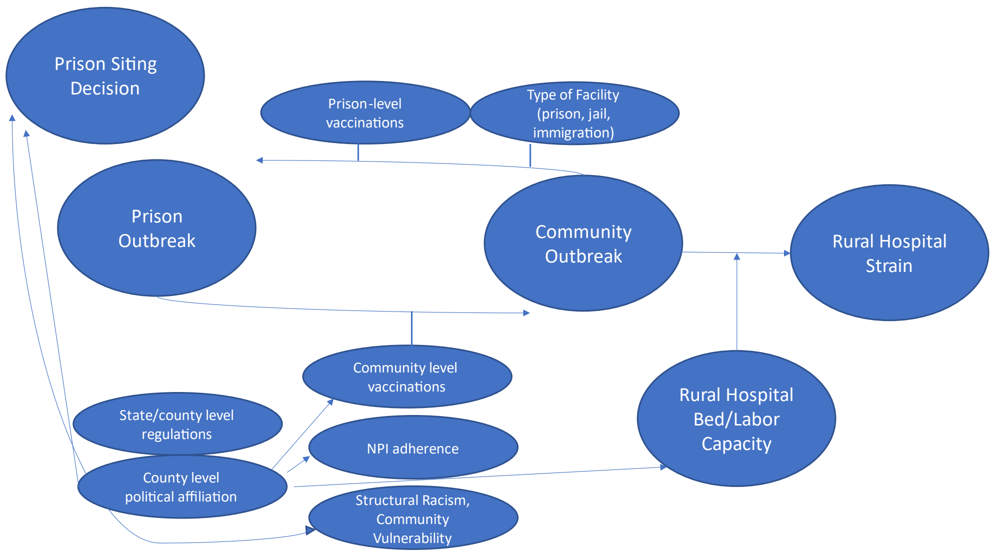
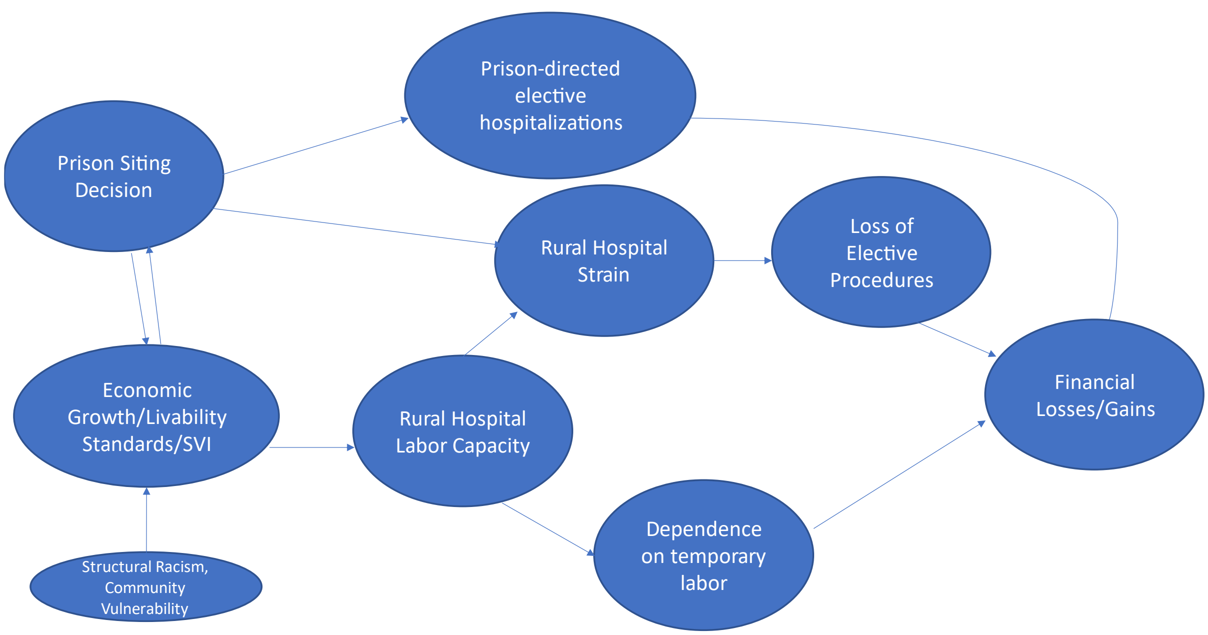


Figure 1. 2: Conceptual Model for Rural Hospital Financial Loss/Gain



Measures
Table 1. 1 Measures

Outcomes	**Measure**	**Time**
Hospital Strain	% beds filled, as reported by the HHS COVID-19 Reported Patient Impact and Hospital Capacity	June 2020-December 2021
Hospital Financial Margins	HCRIS Operating and Profit Margins	2017-2021

Predictor	**Measure**	**Time**
Community Economic Growth/Livability Standards	County-level Social Vulnerability Index	2020
Community NPI Adherence	unmeasured variable	
Community NPI Regulations	State-level Face Mask, Gym, and Restaurant Closure Mandates	
Community Outbreak	County level COVID rates	March 2020-December 2022
County Level Political Affiliation	% of individuals that voted for Republican candidate in the 2016 presidential election from MIT Election labs	2016
Community Vaccination Levels	County-level Vaccination Rates	December 2020-December 20222
Number of Hospital Elective Admissions/Procedures	Unmeasured variable	
Hospital Temporary Labor Dependence	unmeasured variable	
CI Level Vaccinations	UCLA COVID Behind Bars CI vaccination rate; largely unmeasured variable	
CI Outbreak	UCLA COVID Behind Bars CI COVID rate; largely unmeasured variable	
CI Siting	Hospital proximity to CI	
Community population density	2020 Census tract population density	

Aims and Hypotheses

Aim 1: To determine the average difference in weekly probability that general medicine floors and intensive care units in a hospital will be strained in carceral adjacent vs non-adjacent rural hospitals.

H1: Carceral adjacent hospitals will have more strain than non-adjacent hospitals, particularly in communities with greater than 50% of Black, Latino, and Native American populace.

Aim 2: To analyze the difference-in-differences operating margins before and after the fiscal year 2020 between carceral institution and non-adjacent facilities.

H2: Carceral adjacent hospitals will have greater financial losses than non-adjacent hospitals.

Methods

Measures and Data

Outcome

Hospital strain (one of two outcomes) and location data comes from COVID-19 Reported Patient Impact and Hospital Capacity by Facility database of the US Department of Health and Human Services; such data provides hospital geolocation data and weekly strain data for ICU and for general medicine floors from July 2020 to the present. The transformed outcome is binary, indicating whether any hospital ICU unit or general medicine floor is at greater than 100% capacity. Hospital operating margins (the second outcome) from 2017-2021 will be derived from the US Healthcare Cost Report Information System (HCRIS) and are winsorized at the 95th percentile, tracking only hospitals reporting information for all 5 years. This outcome will be used rather than total profit since the federal Pandemic Relief Fund provided large amounts of money to cover operating losses during the pandemic (although more vulnerable hospitals tended to receive less funding) [36].

Covariates

Prison location data are drawn from the UCLA COVID Behind Bars dataset. 2020 county level spatial shapefiles as well as Social Vulnerability Indices (SVI) are drawn from the Centers of Disease Control (CDC). Rurality measures are as defined by the Health Resources and Services Administration, combining data from US Census rural classification and Department of Transportation Rural and Urban Commuting areas. We controlled for census tract population density as calculated by the 2020 Census. Finally, we interacted the primary predictor (ordinal distance from a CI) with a binary indicator indicating greater than 50% of the hospital's census tract population being Black, Latina/o, or Native American by the 2020 US Census (i.e., minority-majority status).

Identification

Rural Hospitals will be identified by their ordinal proximity to a CI, measured by travel distance, with ordinal distance rounded up if within 5 relative minutes. Rural status of a hospital or CI is determined by location in a HRSA identified rural county or census tract. For the purposes of this study the closest three hospitals are assumed to be within the treatment group, accounting for possible network effects and hospital bypassing; the mean distance between CIs and the nearest 3 hospitals was 27 minutes, within range of average distance for rural residents from past work[51].

Analysis

Capacity Strain

The principal outcome is weekly complete (e.g., 100%) adult ICU strain, labeled as a binary outcome, which is estimated by an OLS model with interacted county-month-year fixed effects and clustered standard errors, reflecting the spatiotemporal dynamics of SARS-COV-2 surges throughout the United States between 2020 and January 2022. (A secondary outcome is general ward unit weekly complete strain using the same estimation). In both models we controlled for county vaccination rates, the ratio of ICU or general ward beds to county population, hospital census tract social vulnerability level, and "minority-majority status", i.e., a binary indicator indicating greater than 50% of the hospital's census tract population being Black, Latina/o, or Native American by the 2020 US Census. (Minority-majority status was interacted with ordinal distance.) Finally, we estimated operating margin changes via a 2x2 difference-in-difference regression with baseline periods spanning 2017-2019 and follow-up from 2020-2022; results were stratified by fiscal year period (e.g., January to December, October to September, July to June). We controlled for census-tract-level minority-majority status (again interacted with ordinal distance), census-tract social vulnerability index, and critical access hospital (CAH) status. Operating margins were winsorized at both 2.5th percentiles and we applied county-year interacted fixed effects and clustered standard errors.

Spatial Estimations

To understand spatial variations of this relationship, we used Multiscale Geographic Weighted Regression [52], which provides the results of many local regressions within algorithmically determined geographic bandwidths and were used to determine regions of high intensity of the main and interacted effects. (For the purposes of this analysis, proximity for the 3 closest hospitals was collapsed into a binary variable and the outcome was the percentage of reported weeks of 100% capacity strain).

Sensitivity Analyses and Sub-analyses

Rural hospital strain is generally rare (1.1% among ICU and 0.4% among general wards in this sample), leading to concerns about the applicability of linear probability models in this scenario. We thus trialed Poisson methods for ICU strain in this sensitivity analysis; however, due to problems from perfect prediction given the rarity of the outcome, we also leveraged a Bayesian regression using a weakly informative prior probability, as has been suggested in other literature[53,54].

We pursued several other sensitivity analyses: First, we looked at differences in the percentage of ICU admissions and total ICU beds accounted for by COVID hospitalizations over the study period. Second, since we do not have access to pre-pandemic capacity strain data, we modeled the percentage of time that hospitals were strained above a simulated baseline level, i.e., the median percentage of beds filled when the county was below the 25% percentile of its own recorded cases between June 2020-January 2022. Third, we interact the type of carceral facility (prison, jail, juvenile detention, immigration detention, multi-facility site) with ordinal distance. Fourth, we stratify results between critical access (CAH) and short-term hospitals (STH). Finally, to account for the rarity of the outcome, we adjust the occupancy threshold to 80%, also stratified between CAH and STH. All analyses were conducted using R and Stata 18.0.

Results

Table 1. 2: Descriptions of Rural Hospitals by Proximity to Carceral Institutions

	Closest Hospital	**2nd Closest Hospital**	**3rd Closest Hospital**	**Comparator hospitals**	**All Hospitals**
	(N=674)	(N=441)	(N=300)	(N=769)	(N=2184)
Distance from Nearest Correctional Institution (minutes)					
Median [Q1, Q3]	6.47 [2.87, 14.9]	25.8 [20.4, 31.9]	36.0 [30.1, 43.6]	49.3 [40.3, 65.4]	24.5 [10.8, 38.2]
# General Medical/Surgical Beds					
Median [Q1, Q3]	29.4 [23.4, 63.0]	25.0 [21.0, 39.8]	25.0 [20.0, 36.4]	25.0 [19.6, 30.0]	25.0 [21.0, 42.0]
#Number of Medical ICU Beds					
Median [Q1, Q3]	2.00 [0, 8.00]	0 [0, 5.60]	0 [0, 4.65]	0 [0, 4.00]	0 [0, 6.00]
% county voters for Republican candidate					
Median [Q1, Q3]	0.631 [0.300, 0.746]	0.673 [0.435, 0.764]	0.656 [0.461, 0.767]	0.656 [0.445, 0.761]	0.651 [0.414, 0.756]
Social Vulnerability Index (1 is highest vulnerability)					
Median [Q1, Q3]	0.692 [0.419, 0.886]	0.533 [0.277, 0.726]	0.424 [0.202, 0.695]	0.398 [0.172, 0.647]	0.510 [0.260, 0.757]
% Vaccinated in Surrounding County as of August 2021					
Median [Q1, Q3]	35.4 [29.9, 42.0]	35.9 [30.3, 42.6]	36.1 [30.8, 43.4]	37.5 [32.0, 44.4]	36.4 [30.8, 43.3]
Operating Margin (%)(2017-2019)					
Median [Q1, Q3]	-6.44 [-16.0, 2.82]	-6.13 [-15.5, 1.16]	-5.90 [-14.8, -0.126]	-6.65 [-15.0, 0.492]	-6.36 [-15.2, 1.06]

The study identified 5,091 hospitals, of which 2,184 were designated as rural and 1,384 were rural CI-adjacent (Table 1.2). Analysis also identified 1,687 unique carceral institutions: 1,138 state-level adult prisons, 168 county level jails, 115 federal facilities, 133 immigration detention facilities, and 133 juvenile detention facilities. 839 of these were in rural counties. The 3 closest hospitals were an average of 27 minutes (closest, 14.5 minutes, 2nd, 35.9 minutes, 3rd 45 minutes) from CIs. 242 hospitals were in minority-majority census tracts, of which 54.1% (131) were closest to a CI compared to 27.1 % (519) of hospitals in non-minority-majority Rural hospitals had an average ICU strain rate of 1.1% of all hospital-weeks and general ward strain rate of 0.4% (compared to 1.0% and 0.4% among all contemporaneous hospitals nationwide). Median operating margins over 2017-2019 were -6.36% in rural hospitals.

Non-interacted OLS models largely demonstrated no relationship between CI-adjacency and ICU or general ward strain (ICU strain for closest hospital: -0.40, 95% CI-1.65,0.85, 2nd closest hospital: -0.26, 95% CI-1.42,0.90; 3rd closest hospital: 0.05, 95% CI-0.10,0.20). General ward strain for nearest hospital: 0.28, 95% CI-0.22,0.78, 2nd closest hospital 0.23, 95% CI-0.01,0.47, 3rd closest 0.05, 95% CI-0.10,0.20). However, the interaction of minority-majority status and ordinal distance showed significantly higher rates of ICU strain, particularly 31 percentage points greater for closest hospitals (for closest hospitals 0.31, 95% CI 0.062, 0.558; for 2nd closest hospitals: 0.013, 95% CI -0.013, 0.387; for 3rd closest hospitals; 0.06, 95% CI -0.0172, 0.0295) (Table 2). Logistic and Poisson regression revealed inflated results (eTable 1.1). Bayesian logistic regression models revealed that CI nearest hospitals had a mean odds ratio of strain of 1.19 (95% credible interval, 0.92, 1.52, credible probability 0.91) with a minority-majority distance interaction term of 1.55 (95% credible interval 0.72, 3.33, credible probability 0.86) (eTable 1.2).

There was no statistically significant coefficient within ordinal distance or interacted minority-majority status and ordinal distance variables among general ward strain outcomes (see table 1.3), except for the interaction between second 2nd closest hospitals and minority-majority status (0.45%, 95% CI 0.01%, 0.89%). Average operating margins also did not differ between control groups and proximal hospitals during this period (Figure 5) in average or stratified models, except for a 10.1% (95% CI 2.27, 17.9) and 10.2% (95% CI 3.67, 16.7) differential rise in operating margins among closest and 2nd closest hospitals compared to controls in July strata (eTable 3).

Table 1. 3 Coefficients of ICU and General Ward Strain

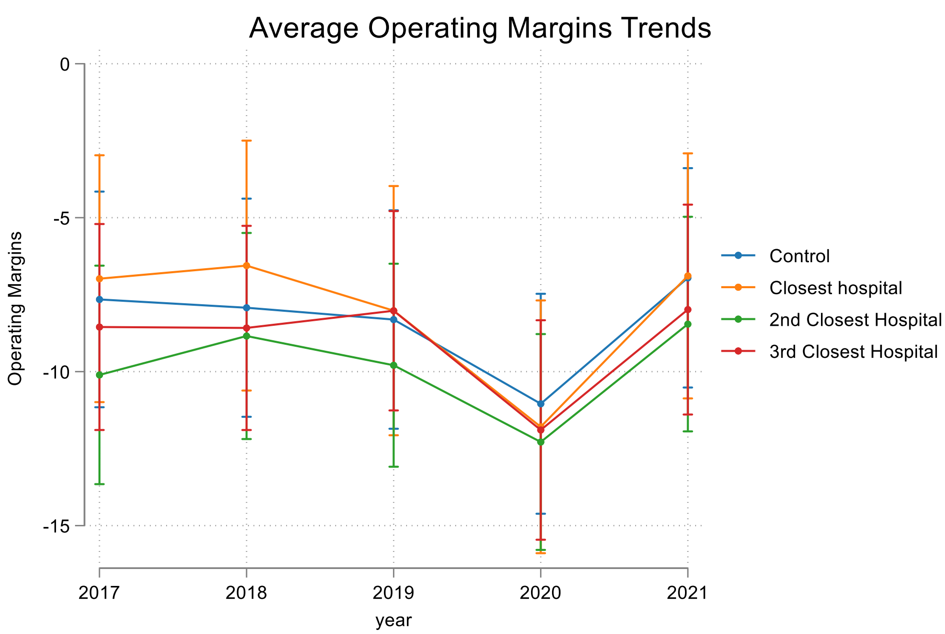
	ICU Strain	ICU Strain	Ward Strain	Ward Strain
Closest Hospital	-0.29 (-1.17, 0.58)	-0.40 (-1.65, 0.85)	0.33 (-0.16, 0.81)	0.28 (-0.22, 0.78)
2nd Closest Hospital	-0.19 (-1.04, 0.66)	-0.26 (-1.42, 0.90)	0.26 (0.02, 0.49)	0.23 (-0.01, 0.47)
Third Closest Hospital	0.13 (-0.61, 0.87)	0.06 (-0.67, 0.80)	0.07 (-0.09, 0.22)	0.05 (-0.10, 0.20)
Minority-Majority Community		-1.08 (-3.44, 1.29)		-0.39 (-0.70, -0.07)*
Closest Hospital*Minority-Majority Community		31.16 (6.35, 55.97)*		0.67 (-0.13, 1.48)
2nd Closest Hospital*Minority-Majority Community		1.39 (-1.20, 3.99)		0.45 (0.01, 0.89)
Third Closest Hospital*Minority-Majority Community		0.68 (-1.66, 3.02)		0.20 (-0.37, 0.76)
% Vaccinated in County	-0.02 (-0.05, 0.01)	-0.02 (-0.05, 0.01)	-0.01 (-0.01, 0.00)	-0.01 (-0.01, 0.00)
Social Vulnerability Index	0.85 (-0.36, 2.05)	0.72 (-0.99, 2.44)	0.23 (-0.02, 0.47)	0.26 (0.01, 0.51)*
[ICU] bed: county population ratio	-0.35 (-0.46, -0.23)	-0.36 (-0.53, -0.19)***		-0.01 (-0.02, -0.01)**
Census Tract Population Density	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)		0.00 (0.00, 0.00)**
Constant	2.85 (1.24, 4.45)	0.18 (-1.88, 2.24)	0.41 (0.08, 0.73)	0.30 (-0.06, 0.66)

*p<0.05, **p<0.01, ***p<0.001

Sensitivity and sub-analyses

Compared to CI-adjacent hospitals in other rural communities, immediately CI-proximal hospitals ICUs in minority-majority communities had a 123.4% (95% CI 115.5%, 131.2%) overall percentage-point increase of patients with COVID and 107.4% (95% CI 98.3%, 116.4%) relative increase of allotted beds occupied with COVID patients (eTable 1.4). They also had a higher percentage of reported weeks (0.45, 95% CI 0.129, 0.760) of having more patients than their simulated baseline (eTable 1.5). Effects were not statistically significant when separated by critical access and short-term hospitals, although at the 80% strain cutoff CI-adjacent non-critical access hospitals were statistically significant and divergent (eTable 1.6-1.7). Finally, among immediately CI-proximal hospitals, hospitals adjacent to juvenile detention facilities (0.04, 95% 0.03, 0.07) and multi-facility sites (0.03, 95% 0.01, 0.05) had a higher probability of being 100% full compared to prison-adjacent hospitals (eTable1.8), which in turn had no difference in jail and immigration detention facilities.

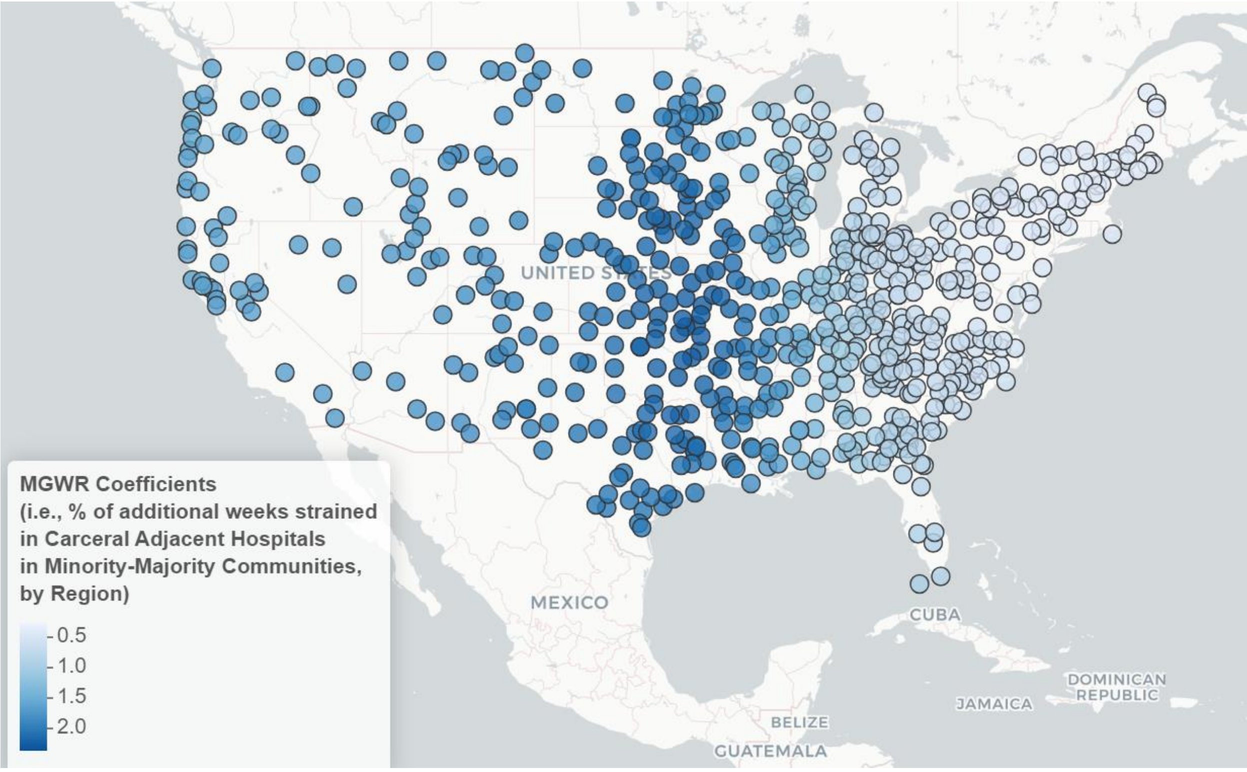
Figure 1. 3: Average Operating Margins Trends, by Carceral Proximity



Spatial Analyses

Multiscale Geographic Weighted Regression (MGWR) showed that the highest intensity of impacts for minority predominant communities was along the Mississippi River Basin, which showed an approximate 2% increase in the number of weeks strained in CI adjacent rural hospitals in minority-majority communities (Figure 1.4), compared to a 0.4% increase in the Eastern Seaboard.

Figure 1. 4: Coefficients of Carceral Proximity Among Minority-Majority (i.e., Black/Latino/Native American majority) Rural Community Hospitals



Discussion

This study demonstrates that carceral-proximal hospitals in rural communities, particularly those that are minoritized, bore higher than normal risk of ICU strain during the pandemic, with overall no increased risk of general wards strain or improved operating margins. ICU strain effects seem to be driven largely by increases in COVID-patients overall and appears robust to various specifications. Finally spatial analysis shows the South, particularly the lower Mississippi Valley, as having the highest relative increase in ICU strain among minority-majority communities. Although OLS and logistic estimation is challenged by the low base rate of weekly strain, Bayesian posterior probability estimates support a higher risk for at CI-proximal hospitals.

The fact that ICUs were more likely to be affected than general wards might reflect either increased community severity of illness or delays in care referral in prisons leading to higher severity of illness, as has been recorded in other literature[55,56]. The observation that minoritized communities are affected might be driven by transmission of COVID via carceral workforce or cycling of imprisoned persons themselves into local communities, which has been demonstrated before[57]. However, John Eason's quantitative and qualitative analyses demonstrate that rural, minoritized communities might request to be sites of prisons for job creation[40,41]. Unfortunately, those very same communities were potentially the hardest hit during the COVID pandemic.

There have been several data analyses of mortality risk within strained ICUs before and during the pandemic, with one study showing that hospitals with greater than 100% of the ICU beds occupied by COVID patients had over two-fold COVID-related mortality compared to hospital this mortality risk might also extend affected hospitals[58]. This might not include the particular risk of Black inpatient mortality recorded within strained hospital units[59].

Work on carceral geography has emphasized the historical linkages between prison spaces, the incarcerated, and local communities[60]. This study attempts to build on past work to better detail the infectious disease spillovers from carceral institutions on local communities their healthcare institutions. This counterbalances research that shows that the prison boom created a jobs program for rural towns without sustained economic benefits and should be kept in mind by locals judging the costs and benefits of maintaining or building carceral institutions. Furthermore, this underlines the reifying effects of structural racism: carceral spaces largely populated by Black and Brown individuals might be causing harm to health systems also dedicated to serve that same population. Further work should detail how other disease networks and healthcare institutions might be impacted near carceral institutions.

One limitation of the study is that we do not have pre-pandemic capacity strain data, and although we attempt to simulate that with COVID-era data, we cannot say that ICU strain levels overall were different from before 2020. However, we do find that ICU admissions in minority-majority communities have an unusually high burden of COVID-infections, ICU occupancy rates spend more time above simulated baselines, and occupancy rates might be sensitive to county-wide increases in COVID-infections.

Conclusion

Carceral-adjacent rural hospitals in minority-majority communities are at high risk of ICU strain during the early stages of the COVID pandemic. Further work must be done to protect rural health systems during further respiratory pandemics, including decarceration, which has shown to reduce community COVID burden in other work[61].

Supplement

eTable 1. 1: Logistic and Poisson Estimates

	Logistic (OR)	Poisson (RR)
Closest Hospital	0.79 (0.23, 2.74)	0.83 (0.21, 3.23)
2nd Closest Hospital	1.06 (0.30, 3.81)	1.06 (0.24, 4.64)
Third Closest Hospital	1.12 (0.38, 3.30)	1.10 (0.49, 2.49)
Minority-Majority Community	4.41×10^{-7} (0.00, .)	5.19×10^{-7} (6.09×10^{-8}, 4.41×10^{-6})***
Closest Hospital*Minority-Majority Community	7.97×10^{19} (0.00, .)	3.75×10^{16} (10.4×10^{15}, 1.35×10^{18})***
2nd Closest Hospital*Minority-Majority Community	2.52×10^{11} (0.00, .)	1.68×10^{11} (7.17×10^{9}, 3.94×10^{12})***
Third Closest Hospital*Minority-Majoirty Community	1.00 (0.00, 0.00)	1.00 (0.00, 0.00)
% Vaccinated in County	0.97 (0.93, 1.02)	0.99 (0.97, 1.00)
Social Vulnerability Index	5.98 (0.86, 41.74)	5.27 (0.71, 39.22)
ICU bed: county population ratio	0.50 (0.38, 0.64)***	0.56 (0.36, 0.87)*
Census Tract Population Density	1.00 (1.00, 1.00)	1.00 (1.00, 1.00)

*p<0.05, **p<0.01, ***p<0.001

eTable 1. 2: Bayesian Coefficients (with credible intervals)

Closest Hospital	1.19 (0.93, 1.52)
2nd Closest Hospital	1.19 (0.89, 1.59)
Third Closest Hospital	0.95 (0.69, 1.31)
Minority-Majority Community	1.19 (0.58, 2.42)
Closest Hospital*Minority-Majority Community	1.55 (0.72, 3.33)
2nd Closest Hospital*Minority-Majority Community	0.43 (0.16, 1.14)
Third Closest Hospital*Minority-Majoirty Community	2.44 (1.01, 5.91)
% Vaccinated in County	1.01 (1.01, 1.02)
Social Vulnerability Index	1.55 (0.95, 2.53)
ICU bed: county population ratio	0.79 (0.74, 0.85)

eTable 1. 3: Operating Margins

	Average	January-December Fiscal year	July-June Fiscal Year	October-September Fiscal Year
Closest hospital	2.41 (-2.00, 6.81)	-8.61 (-17.62, 0.40)	-3.23 (-9.74, 3.28)	2.12 (-6.42, 10.66)
2nd Closest Hospital	-0.86 (-4.37, 2.64)	-6.09 (-15.25, 3.07)	-2.73 (-7.42, 1.96)	3.81 (-3.10, 10.73)
3rd Closest Hospital	1.26 (-2.10, 4.61)	-4.09 (-12.28, 4.09)	-0.02 (-4.56, 4.52)	1.40 (-3.75, 6.55)
Post-2020	*Absorbed by fixed effects*			
Ordinal distance# Post-2020				
Closest hospital# Post-2020	-3.24 (-10.64, 4.16)	3.83 (-12.29, 19.95)	10.10 (2.02, 18.18)*	-9.81 (-20.59, 0.98)
2nd Closest Hospital# Post-2020	-1.56 (-7.75, 4.64)	1.71 (-14.13, 17.54)	10.18 (3.46, 16.89)**	-6.93 (-16.11, 2.25)
3rd Closest Hospital# Post-2020	-4.15 (-10.14, 1.84)	4.29 (-9.09, 17.67)	4.44 (-1.85, 10.72)	-8.10 (-17.12, 0.93)
Type of Hospital (base: Critical Access, 1: short term)	2.08 (-0.10, 4.25)	1.60 (-1.75, 4.95)	-5.69 (-11.24, -0.15)*	-5.98 (-9.10, -2.87)***
Census Tract Social Vulnerability Index	-10.70 (-17.63, -3.77)**	-14.73 (-23.89, -5.57)**	-3.38 (-18.45, 11.69)	-3.00 (-22.11, 16.10)
Constant	-0.47 (-0.80, -0.14)	1.23 (-7.79, 10.26)	3.00 (-7.67, 13.66)	-0.13 (-11.45, 11.18)

*p<0.05, **p<0.01, ***p<0.001

eTable 1. 4: COVID-specific ICU changes

	(%) ICU Beds filled with COVID Patients	(%) patients with COVID
Closest Hospital	-4.02 (-6.75, -1.30)**	-5.26 (-8.66, -1.85)**
2nd Closest Hospital	-6.77 (-9.42, -4.11)***	-7.49 (-10.89, -4.08)***
Third Closest Hospital	-4.10 (-6.21, -1.99)***	-2.53 (-5.46, 0.40)
Minority-Majority Community	-13.45 (-20.77, -6.13)***	-27.93 (-35.47, -20.39)***
Closest Hospital*Minority-Majority Community	107.44 (98.41, 116.46)***	124.44 (116.52, 132.36)***
2nd Closest Hospital*Minority-Majority Community	23.84 (14.16, 33.53)***	41.94 (31.77, 52.12)***
Third Closest Hospital*Minority-Majority Community	5.77 (-2.70, 14.24)	24.53 (12.65, 36.41)***
% Vaccinated in County	-0.23 (-0.28, -0.17)***	-0.25 (-0.34, -0.17)***
Social Vulnerability Index	1.15 (-3.14, 5.44)	-0.39 (-5.56, 4.78)
ICU bed: county population ratio	0.03 (-0.29, 0.36)	-0.81 (-1.19, -0.42)***
Census Tract Population Density	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)

*p<0.05, **p<0.01, ***p<0.001

eTable 1. 5: Percentage of Time spent above simulated baseline

Closest Hospital	-12.76 (-19.56, -5.95)***
2nd Closest Hospital	-13.99 (-20.26, -7.73)***
Third Closest Hospital	-6.60 (-12.26, -0.94)***
Minority-Majority Community	-18.68 (-35.96, -1.40)***
Closest Hospital*Minority-Majority Community	43.80 (12.42, 75.18)*
2nd Closest Hospital*Minority-Majority Community	27.01 (5.37, 48.66)***
Third Closest Hospital*Minority-Majority Community	17.81 (-4.08, 39.70)*
% Vaccinated in County	-0.32 (-0.48, -0.16)***
Social Vulnerability Index	-4.66 (-15.23, 5.92)**
ICU bed: county population ratio	-3.81 (-4.71, -2.91)*
Census Tract Population Density	0.00 (0.00, 0.00)

*p<0.05, **p<0.01, ***p<0.001

eTable 1. 6: Critical Access and Short-Term Hospitals

	Critical Acccess Hospitals	**Short Term Hospital**
Closest Hospital	0.01 (-0.01, 0.02)	0.01 (-0.01, 0.02)
2nd Closest Hospital	0.00 (-0.01, 0.02)	0.00 (-0.01, 0.02)
Third Closest Hospital	0.01 (0.00, 0.02)	0.01 (0.00, 0.02)
Minority-Majority Community	0.01 (-0.02, 0.03)	0.01 (-0.02, 0.03)
Closest Hospital*Minority-Majority Community	*Collinear with fixed effects*	*Collinear with fixed effects*
2nd Closest Hospital*Minority-Majority Community	0.00 (-0.02, 0.02)	0.00 (-0.02, 0.02)
Third Closest Hospital*Minority-Majority Community	*Collinear with fixed effects*	*Collinear with fixed effects*
% Vaccinated in County	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
Social Vulnerability Index	0.01 (-0.02, 0.03)	0.01 (-0.02, 0.03)
ICU bed: county population ratio	0.00 (-0.01, 0.00)**	0.00 (-0.01, 0.00)**
Census Tract Population Density	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)

*p<0.05, **p<0.01, ***p<0.001

eTable 1. 7: Strain at 80% threshold

	Overall Effect	**Critical Acccess Hospitals**	**Short Term Hospital**
Closest Hospital	-0.01 (-0.08, 0.07)	-0.32 (-0.48, -0.16)***	0.32 (0.23, 0.41)***
2nd Closest Hospital	-0.06 (-0.14, 0.01)	-0.31 (-0.45, -0.18)***	0.29 (0.19, 0.39)***
Third Closest Hospital	0.01 (-0.05, 0.08)	-0.14 (-0.25, -0.03)*	0.26 (0.17, 0.36)***
Minority-Majority Community	0.17 (0.01, 0.34)*	0.06 (-0.14, 0.25)	-0.36 (-0.54, -0.19)***
Closest Hospital*Minority-Majority Community	0.11 (-0.29, 0.50)	*Collinear with fixed effects*	*Collinear with fixed effects*
2nd Closest Hospital*Minority-Majority Community	-0.11 (-0.35, 0.13)	*Collinear with fixed effects*	0.80 (0.56, 1.03)***
Third Closest Hospital*Minority-Majority Community	-0.46 (-0.67, -0.25)***	*Collinear with fixed effects*	*Collinear with fixed effects*
% Vaccinated in County	0.00 (0.00, 0.00)**	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)**
Social Vulnerability Index	0.06 (-0.05, 0.16)	0.67 (0.45, 0.90)***	-0.07 (-0.22, 0.07)
ICU bed: county population ratio	-0.01 (-0.02, -0.01)**	-0.05 (-0.07, -0.03)***	-0.02 (-0.04, -0.01)***
Census Tract Population Density	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)***	0.00 (0.00, 0.00)***

*p<0.05, **p<0.01, ***p<0.001

eTable 8: Interaction with Facility and Type of Facility

Closest Hospital	-0.02 (-0.03, 0.00)
2nd Closest Hospital	0.01 (0.00, 0.02)
Third Closest Hospital	0.00 (-0.01, 0.01)
County/Jail	----
Immigration	0.01 (-0.01, 0.04)
Juvenile	--
Two or More Facilities	-0.01 (-0.02, 0.00)
Closest#County/Jail	-----
Closest #Immigration	0.00 (-0.03, 0.04)
Closest #Juvenile	0.04 (0.01, 0.07)*
1#Two or More Facilities	0.03 (0.01, 0.05)*
2#County/Jail	---
2#Immigration	-0.02 (-0.04, 0.00)*
2#Juvenile	---
2#Two or More Facilities	-0.01 (-0.03, 0.00)
3#County/Jail	----
3#Immigration	---
3#Two or More Facilities	--
% Vaccinated in County	0.00 (0.00, 0.00)
Social Vulnerability Index	0.00 (-0.02, 0.02)
ICU bed: county population ratio	0.00 (-0.01, 0.00)***
Census Tract Population Density	0.00 (0.00, 0.00)
Constant	0.02 (0.01, 0.04)

*p<0.05, **p<0.01, ***p<0.001

Chapter 2: The Mobility Transition in Physician Migration

Abstract:

Introduction: Physician migration is a problem of international concern, and studies have attempted to determine whether macroeconomic and developmental factors that might predict nationwide decreases in physician migration. Like the nutritional and epidemiologic transitions, there is an understood "migration transition" as well, with migration levels for highly educated individuals decreasing with increasing national income. This phenomenon has not been studied for physicians, however, and can provide insights into the macroeconomic determinants and prediction of emigration.

Methods: We drew 2000-2019 physician annual new migrant data (i.e., flows) from the Organization for Economic Co-operation and Development (OECD), converted it into logged, year lagged-annual physician emigration flows (annual new migrants), and charted it against logged origin country real GDP per capita (2017 international dollars). We fit an ordinary least squares (OLS) model and gravity model testing the relationship between the year-lagged natural log of real GDP per capita and the natural log of total annual emigration flows separately in OLS quadratic model and gravity model analysis. Both models included an interaction with geographic regions.

Results:

We analyzed 1,887 country-years of data from 138 countries. Across countries, we found a statistically significant quadratic relationship (quadratic coefficient 0.19, 95% CI 0.03, 0.35) between GDP per capita and annual physician emigration flows. Descriptive results disaggregated by region of the world show that as GDP rises migration flows generally decline in East Asia & the Pacific, generally increase in Europe, are bimodal in the Middle East and North Africa, and remain the same in Latin America and sub-Saharan Africa. Gravity models demonstrates no overall

quadratic effect and a negative linear effect, with linear GDP-related declines in emigration in Latin America, the European Union (EU), Central Asia, and South Asia, a quadratic relationship in the Middle East and North Africa and North America, and no relationship in sub-Saharan Africa and non-EU European countries, although lagged results demonstrated a delayed positive linear GDP-emigration relationship in non-EU European countries.

Conclusion:

The relationship between national income and physician migration is complex and depends partially on geographic factors and destination country-origin country interactions.

Introduction

Physician emigration from low- and middle-income countries (LMICs) to high income countries is a topic of great concern to LMIC policymakers[62]. It is estimated that 27.2% of all physicians in Organization for Economic Co-operation and Development (OECD) nations were of foreign origin in 2015[63], many of whom have come from countries with physician shortages [64]. An analysis of physician migration from nine sub-Saharan African countries estimated that the training costs of physicians who went to medical school in those countries but were practicing in OECD nations as of 2010 exceeded $2 billion in publicly funding medical education expenditures[65]. Another analysis accounting for the lifetime practice of a physician places that estimate at $15 billion annually in low- and middle-income countries (LMICs).[66] Concern for this phenomenon led to the World Health Organization Global Code of Practice on the International Recruitment of Health Personnel, which was approved unanimously by the World Health Assembly as the second global code of practice ever affirmed since its creation in 1948[21].

There are models for migration that might help predict future physician emigration from developing countries. From the point of view of low- and middle-income countries, emigration rates for the general population (across all professions, not just health workers) follow an inverted U-shaped curve, with migration rising at an inverse relationship to GDP per capita until source countries reach a GDP per capita of $7,000-$8000 PPP (2011 international dollars) or more, after which emigration rates fall. This phenomenon, called *the mobility transition*, was theorized initially in 1971 and has been examined repeatedly, including confirmation as a cross-country phenomenon recently by Clemens [67,68]. Further research has attributed an important part of this paradoxical increase in emigration with increased GDP to increased skill acquisition within source counties at first leading to increased international competitiveness and increased emigration and followed by a decline in emigration when local opportunity costs of emigration outweigh the perceived gains from emigration[22]. However, for highly educated emigrants, OECD research indicates a different migration transition, with emigration rates falling monotonically with increased GDP per capita across the country income spectrum[23].

The negative relationship between GDP per capita and physician emigration rates has been debated in the literature. One time-series study based on gravity modeling using physician registration data to 22 destinations from 1991-2014 showed an origin country income elasticity of emigration of -0.236 (i.e., a 0.23% relative decrease in emigration with every 1% increase in GDP), but there was no differentiation between different origin countries, and data used total counts (stocks) of migration instead of annual new entrants (flows)[69]. Declines in stocks might be due to deaths, retirement, and return. Further work has focused on flows but focuses on time-varying destination country factors instead of time-varying origin country factors such as GDP[70]. Finally, a cross country study of physicians who emigrated to the United States, Canada, Australia, and the United Kingdom from 1999 to 2004 demonstrated an increase in emigration with increasing GDP per capita[71]. However, this study used an unusual measure of emigration, emigration density (physician emigres per 1000 population of origin country), which might be confounded by origin country changes in physician supply [72].

Determining if there is a mobility transition is important since an accurate prediction of future emigration flows is necessary for health workforce planning. In the most recent 10-year projection of global health workforce needs, future migration was assumed to be constant for all countries over time, regardless of economic growth[72]. In the following study, we analyze trends of international physician emigrant data drawn from OECD nations. We examine physician emigration flows (i.e., annual number of new physician emigrants) and its relationship with GDP per capita from source (i.e., origin) countries to see if there is a linear or more complex relationship between the two variables. A secondary outcome is to determine whether separate geographic origin regions might alter this relationship.

Our hypothesis is that there is a general decline in emigration with increasing GDP per capita across geographic regions (consistent with prior research).

Study Aims

Aim 1: To determine if there is a relationship between GDP per capita and physician emigration across countries and years.

Hypothesis 1: There is a general decline in emigration with increasing GDP per capita.

Aim 2: To investigate the mechanism of any such relationship.

Hypothesis 2a): The strength of the GDP-emigration relationship is heterogeneous but negative across geographical regions.

Hypothesis 2b) Countries with high dependence on public sector healthcare and lower levels of overall healthcare spending might have higher levels of physician emigration.

Conceptual Model

There are various economic and sociological models for migration, all of which provide a partial picture of the determinants of international migration. The first model is the neoclassical theory, which posits that emigration is only driven by individual-level changes in incomes between destination and origin countries. The second theory, the new economics of labor migration, builds on that and posits that immigration is an investment to generate the family wealth of relatives left behind. Dual labor market theory describes immigration as driven by high-income countries in order to fill "lower-strata" jobs that native professionals are not interested in (e.g., agricultural labor or rurally placed physicians). This is partially complementary to world systems theory which divides the world into "core" (wealthy, heavily industrialized) and "periphery" (poorer, less-industrialized) nations. Because of globalization, core nations invest capital to extract resources from periphery countries, which might over the long run cause destabilizing conditions that drive emigration from periphery to core [73]. "Semi-periphery" countries (e.g., BRICS countries) are in between the two categories—influenced by core countries and able to exert influence on peripheral nations.

Qualitative and survey data of physicians specifically further identify several important "push" (i.e., origin country) and "pull" (destination country) factors that determine migration. Push factors include remuneration differentials between destination and origin countries, opportunities for career in a high-income country, and dissatisfaction with current practice. Pull factors are related to strong demand in the destination country, recruitment efforts, and agreeable migration policy.[74] One study demonstrated similar emigration rationales for physicians who migrated from the United Kingdom and those that came to the United Kingdom, demonstrating that similar forces propel physicians from low, middle-and high-income countries[75]. Choices of destination country are linked to similarities of language and higher diaspora concentration[69].

While these specific micro-level factors might be difficult to assess with current datasets, there are some macro-level measurable factors that might be correlated with physician emigration. On the origin-countryside, first and foremost is the relationship between GDP and emigration, as described in the introduction. Health workforce density is another macro-level determinant of emigration, with studies showing that higher health workforce density is correlated with higher emigration rates and may be related to low capacity for hiring new medical graduates[69,71,74]. Civil unrest is also related to increased rates of health professional emigration[76]. Small island countries also have high emigration rates, and increased foreign health aid in the form of technical assistance was also related to decreased emigration[69,77]. Increased HIV prevalence and child mortality rate might be related to decreased emigration, although causality may be hard to determine[71]. Destination-country side aging populations, decreased unemployment, increased spending on health, pre-existing physician shortages low density of doctors, and increased hospital capacity were all shown to be related to higher rates of immigration of foreign physicians [78,79].

How these factors are related to each other as primary causes, mediators and moderators is unclear, and might shift from person to person or country to country. However, Figure 2.1 attempts to organize them into theory-based, macro, and micro level factors. Corresponding measures are represented in Table 2.1.

Finally, there are several factors that are likely correlated with GDP per capita, most prominently overall health spending, with research showing an increase of 0.5% in health spending per 1% increase in GDP per capita for middle- and high-income countries[80]. However, there are several other transitions that might occur with GDP per capita, including a nutritional transition from low calorie to high calorie foods (and at times, malnutrition), a population transition to lower national fertility rates, and an epidemiologic transition from a highly prevalent infectious diseases into highly prevalent chronic non-communicable disease[81–83]. Climate change has been shown to have an increasing impact on nutrition and disease prevalence, which might complicate the transition for impacted countries [84]. These can all confound the relationship between physician migration and GDP per capita.

Figure 2. 1: Conceptual Model

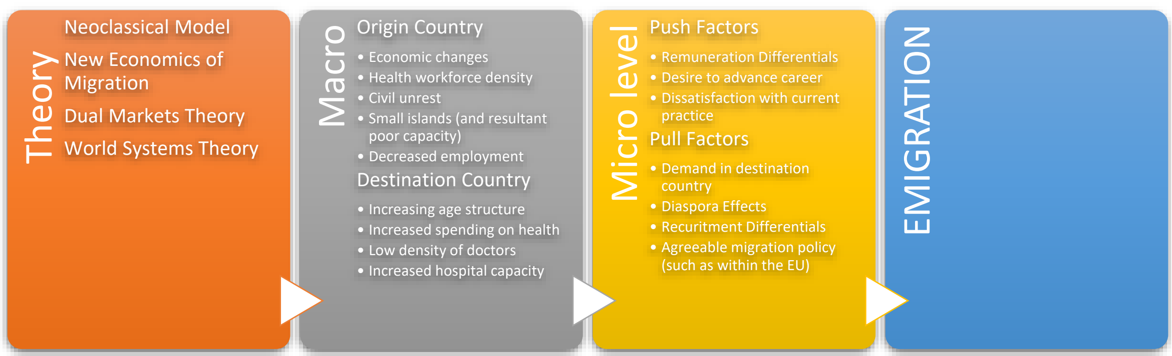


Table 2. 1: Variables

Theoretical Variable	**Operationalized by Variable**
Physician Emigration	Emigration rate
Country-Level Development Opportunity costs of emigration	Ln(GDP per capita)
Physician density	Physicians per source-country 1000 people (in quadratic and linear terms)
European Union Membership	Country years of membership in the EU or Schengen area
Size of the private healthcare market	Domestic private and public healthcare spending
Colonial Links	National Language
HIV prevalence	Not operationalized
Civil Conflict	Country year of coup or conflict (with 1000 deaths), and the year afterward
Island Status	Membership in Small Island Developing States
Origin Country Medical School concentration “Feeder Medical Schools	Herfindahl-Hischmann Index of medical schools of emigrated physicians registered to

	practice in the United Kingdom (2005-2023), by country
Gender composition of physician emigrants	Proportion of emigrated physicians registered to practice in the United Kingdom (2005-2023) who are women, by country
Specialization Rate of physician emigrants	Percent subspecialized of emigrated physicians registered to practice in the United Kingdom (2005-2023), by country

Methods

Data & Measures

Data will be drawn from OECD data on physician emigration flows from 2000-2019. Emigration data is drawn from physician licensure data from OECD member and associate countries. Physician license registries of destination countries are a reliable means of measuring physician emigration and provide a more complete picture than survey data. Furthermore, data on annual new entrants (flows) are more reliable than measuring the annual change in stocks (i.e., total current emigres) since, as mentioned before, flows assess in real time the number of physicians registered instead of having such changes inferred. Doctors are identified by their country of undergraduate medical school training.

This is an observational panel analysis study. Our primary outcome is the income elasticity of emigration, which would be represented as the percent change in emigration rates per 1% change in GDP per capita:

$$Income\ Elasticity = \frac{\%\ relative\ change\ in\ emigration\ rates}{1\%\ change\ in\ GDP\ per\ capita}$$

This will be estimated by the natural log of country specific emigration rates as a primary outcome and using the log GDP per capita as a primary regressor. This is a departure from past literature on the mobility transition, which examined the *simple change in emigration rates* for a population per unit change in logged-GDP per capita. However measuring the income elasticity of emigration makes the output more understandable and uses a unit readily used in other econometrics literature.

We use the following measures. First, we calculate physician emigration rates in the following fashion:

$$Annual\ Emigration\ Rate = \left(\frac{D}{D+S}\right)$$

where *D* represents the number of source country-trained physicians who newly registered in *destination* OECD countries each year and *S* represents the number of physicians registered in the *source* country the same year. *D* is derived as the sum of physician emigrants from all OECD nations; for years that OECD nations did not report their values to the OECD, a zero was assumed. Physicians per 1000 (*S)* was interpolated for a maximum of 6 consecutive missing values. This technique has been used in other health workforce projection literature[85].

GDP per capita is defined in terms of 2017 international dollars, purchasing power parity, to control for inflation and for cross-country differences in purchasing power. Data is drawn from the World Bank Data Bank. While GDP is a more ecological measure than physician incomes, it has been used successfully to predict gross trends in emigration from LMICs. We draw data on public and private health expenditure amounts per capita (2017 international dollars, purchasing power parity) and physician density (per 1000 people) from the World Health Organization. We also created a dummy variable to indicate country-years where a country was a member of the Schengen area and the European Economic Area (EEA), given lower internal restrictions on labor mobility within the EEA area.

As stated in the conceptual model, islands have elevated physician emigration rates. As such we constructed a dummy variable for nations that are part of the Small Island Development

States, an UN-designated group of island nations that have small populations and "narrow resource bases, dominance of economic sectors that are reliant on the natural environment, limited industrial activity, physical remoteness, and limited economies of scale."[86]

Conflict and Coup data for the period was drawn from the UCDP/Armed Conflict Dataset, developed by the International Peace Research Institute of Oslo, Norway and the University of Uppsala, Sweden. Conflict is designated as a year when more than 1000 civilian battle-related deaths occurred in each country. A coup is designated as any year in which a coup attempt took place. I constructed a dummy variable to designate any year in which there was a country and coup as well as lagged dummy variable to indicate the year after a coup or conflict.

Other variables used in a gravity model, including identifying former colonial links and common major languages were drawn from the CEPII database[87]. Destination country diaspora size was drawn from the United Nations Population Division. Selected wage and patient utilization data was drawn from the OCED. UK physician data was drawn from the United Kingdom List of Registered Medical Practitioners, 2005-2023.

Models

We use 4 models to estimate our results. Model 1 represents a naïve conditional OLS model:

Model 1 represents a fixed effects model with the primary regressor as a quadratic and linear coefficient of the log GDP, controlling for log percentage of GDP spent on healthcare spending, with additive country and year fixed effects.

$$\ln(emigration) = \beta_0 + \beta_1 Ln\left(\frac{GDP}{cap}\right)_{i,j} + \beta_2 Ln\left(\frac{GDP}{cap}\right)^2_{i,j} + \beta_3 Ln(healthcare\ (\%\ of\ GDP)_{i,j} + \beta_4 Ln(physicianspercapita)_{od,t-5} + e_{i,j}$$

Model 2-4 will represent gravity models. Gravity models are based on a random utility maximization framework of migration (i.e., that a migration decision will depend on destination country attractiveness, cost of migration, and lost utility by leaving an origin country), and model the likelihood of choosing to migrate to one country or another (or not leave at all). They have been used in other physician migration analyses in part due to their ability to disaggregate origin and destination country factors [70]. We use a Pseudo-Poisson Maximum Likelihood estimator in this model below, with interacted origin country and destination country fixed effects (to account for time-invariant unobserved factors in origin-destination country relationship, such as medical license recognition, fixed bilateral migration policies, and historical national linkages)[88] with added year effects and clustered standard errors at the origin country level. While other work uses origin country-year and destination country-year fixed effects[79,89], this approach would be collinear with GDP per capita, which is the regressor of interest.

$$\ln(emigrantcount) = \beta_0 + \beta_1 Ln\left(origin\frac{GDP}{cap}\right)_{od,t-1} + \beta_2 Ln\left(origin\ \frac{GDP}{cap}\right)^2_{od,t-1} + \beta_3 Ln(healthcare\ (\%\ of\ GDP)_{od,t-1} + \beta_4 Ln(physicianspercapita)_{od,t-5} + \beta_5 EU\_Schengen_{od,t-1} + \beta_6 Ln\left(destination\frac{GDP}{cap}\right)_{od,t-1} + \beta_7\, coloniallink_{od} + \beta_8\, distance_{od} + \beta_9\, commonlanguage_{od} + \beta_{10}\, Ln(migrantstock)_{od,t-5} + \beta_{11} EU_{od,t-1} + e_{od,t} + \ln\ (physician\ count)_o$$

These models include covariates for origin and destination GDP per capita, joint origin/destination country inclusion in Schengen visa area and the European Union, destination country total migrant count (5 years lagged to avoid reverse causality) and origin country physicians per capita (also 5 years lagged). The offset, $\ln(physician\ count)_o$, represents the logged sum of all departed and remaining physicians. Origin country GDP per capita is centered around a grand (i.e., cross-country) mean for Models 1-3. Model 3 is identical except for the exclusion of the quadratic origin GDP per capita term. Model 4 is identical to Model 3 but adds an interaction for region of the world to origin GDP per capita; GDP per capita is also regionally centered for better interpretation.

We undertake four sensitivity analyses: First, all variables in Model 4 are lagged up to 5 years. Second, we estimated Model 4 with destination country-year + origin country fixed effects (to account for unobserved temporal changes in destination country policies and settings). Third, we re-estimated Model 4 additive origin country, destination country, and year fixed effects to account for unrelated destination, origin and year variables. Finally, we compare complete models interacting region with Quadratic and Linear OLS and gravity models.

Descriptive Sub-Analyses

Insomuch as a migration transition in physician migration might defy or confirm conventional predictions on the correlation of national income with physician emigration, the mechanism behind this phenomenon is of some interest. The next section represents a series of tests to determine the mechanism for GDP-emigration trends.

1. Public/Private Sector Healthcare Spending

Before physicians migrate, they examine alternative options, particularly whether or not they are able to attain their goals with domestic work. Depending on governmental priorities and planning required in public sector health provision, it can be underfunded relative to patient demand. In settings with underfunded public health sectors and well-funded private health sectors, physicians might theoretically transfer employment to the private sector, at least part or full time. (Multiple studies have shown that physicians across national contexts might switch to dual practice or to the private sector from the public sector due to concerns that mirror those that precede emigration: financial incentives, career development, infrastructure and staffing, professional work environment, workload, and autonomy.[90]) However in underfunded public health sectors with smaller private sector markets, physicians might instead decide to move overseas. This latter case may be true in both low-income countries and high-income countries where the public provision of healthcare is significant.

2. Origin-destination country shifts

It is not clear to what degree physicians might shift their preferences of destination as their origin countries develop. This has implications not only for understanding the mechanisms of migration flow changes, but also interpretation of gravity analyses themselves, which account for time, origin and destination country fixed effects and might produce biased estimates if the destination countries change with increasing GDP per capita. This analysis will categorize physician migration transitions, particularly from Europe by their destination countries.

3) Individual level characteristics

For this analysis, we will use data from the United Kingdom General Medical Council List of Registered Medical Practitioners from 2005-2023. This data is advantageous not only because of the data on individual level characteristics of international medical graduates and the high number of international medical graduates in the United Kingdom (36%),[91] but because our data shows that as countries increase their GDP, the destinations of physician migration shifts from France and Germany to the United Kingdom and Canada. We will trend the concentration of medical school among emigres (using country-specific Herfindahl-Hisrchman index to see if there is a growth of "feeder schools"), subspeciality choice (i.e., specialties outside of general practitioner, family medicine, general internal medicine, geriatrics, or general pediatrics), and gender composition by GDP to determine whether there are changes in the concentration of medical schools (due to more or less "feeder schools") and sub-specialized physicians or in gender composition among migrants as their origin countries become more wealthy, potentially explaining migration changes.

Results

We analyzed 1,887 country-years of data from 138 countries and 25 destination countries. In Figure 2.2, the unadjusted LOWESS plot demonstrates the quadratic relationship between GDP per capita and emigration. However, as seen in Figure 2.3 there are significant differences between regions of origin, with quadratic relationship being replicated in East Asia and Pacific but a positive, stepwise relationship between GDP per capita and emigration rates in non-EU countries in Europe and Central Asia. There does not appear to be a relationship between GDP and emigration rates in Latin America, sub-Saharan African or South Asia.

Table 2. 2: Model Results

	Quadratic OLS (Model 1)	Quadratic Gravity Model (Model 2)	Linear Gravity Model (Model 3)	Linear Gravity Model w/ Regional Interactions (Model 4)
Ln(Origin GDP)$^2_{t-1}$‡	0.19 (0.03, 0.35)*	0.09 (-0.15, 0.39)	--	
Ln(Origin GDP)$_{t-1}$‡	-3.96 (-6.84, -1.07)**	-2.30 (-6.78, 2.17)	-0.76 (-1.25, -0.28)**	
% of GDP in health spending$_{t-1}$‡	-0.02 (-0.44, 0.39)	-0.13 (-0.62, 0.37)	-0.12 (-0.64, 0.41)	-0.20 (-0.71, 0.31)
Ln(Origin GDP)$_{t-1}$* Central Asia‡				-1.04 (-1.59, -0.50)***
Ln(Origin GDP)$_{t-1}$*EU‡				-1.06 (-1.51, -0.62)***
Ln(Origin GDP)$_{t-1}$ *Europe (non-EU) ‡				-0.07 (-0.74, 0.60)
Ln(Origin GDP)$_{t-1}$ *East Asia and Pacific‡				-0.70 (-1.17, -0.23)**
Ln(Origin GDP)$_{t-1}$ *Latin America‡				-1.95 (-3.27, -0.63)**
Ln(Origin GDP)$_{t-1}$*Middle East and North Africa‡				0.72 (-0.98, 2.42)
Ln(Origin GDP)$_{t-1}$ *North America‡				-2.51 (-3.62, -1.41)***
Ln(Origin GDP)$_{t-1}$ * South Asia‡				-1.40 (-1.86, -0.94)***
Ln(Origin GDP)$_{t-1}$ *sub-Saharan Africa ‡				-0.37 (-0.87, 0.13)

Joint Schengen$_{t-1}$†	--	0.56 (0.27, 0.84)***	0.57 (0.29, 0.86)***	0.53 (0.28, 0.78)***
Ln(Destination GDP)$_{t-1}$‡	---	1.98 (0.83, 3.12)**	2.04 (0.90, 3.18)***	1.86 (0.77, 2.95)**
Joint EU Member$_{t-1}$†	---	0.86 (0.48, 1.24)***	0.90 (0.49, 1.30)***	---
Ln(Diaspora Size)$_{t-5}$‡	---	0.09 (-0.09, 0.27)	0.10 (-0.08, 0.28)	0.12 (-0.04, 0.28)
Ln(Physicians per Capita)$_{o,\ t-5}$‡	-0.27 (-0.55, 0.01)	-0.29 (-0.63, 0.05)	-0.30 (-0.64, 0.03)	-0.17 (-0.41, 0.08)
Fixed effects	Origin country, year	Origin country*destination country+ year	Origin country*destination country+ year	Origin country*destination country+ year
Standard Errors	Origin country	Origin country*destination country	Origin country*destination country	Origin country*destination country
Centering	Grand Mean	Grand Mean	Grand mean	Region

*p<0.05, **p<0.01, ***p<0.001

‡Elasticities, i.e., % change in physician migration for every 1% change in prediction in linear models.

†Can be converted to semi-elasticities. i.e, with conversion ($e^{\text{coefficient}}$-1)*100 can be interpreted as % change for one-level change in predictor.

These results partially reproduce when examined at the country level (see Figures 2.4-2.9, with plotted logarithmized annual migration rates and GDP per capita). In particular, there is a negative naïve relationship across most countries in the South Asia and East Asia and Pacific region and positive relationship within Europe, particularly within Balkan and Eastern European nations. The MENA region is divided between positive (e.g., Morocco, Iran, Tunisia) and negative (Kuwait, Saudi Arabia, Israel) relationship countries, divided by a GDP per capita of $22,000. On average, there does not appear to be a consistent naïve relationship between GDP per capita and migration in Latin America and sub-Saharan Africa (Figures 2.8 and 2.9).

Figure 2.10 shows the quadratic relationship shown in Figure 2 reproduces across destination countries. However, when analyzed compositionally (as the percent of all emigrated physicians instead of the aforementioned rate of migration, Figure 2.11), it appears that physicians from wealthier countries might be opting to migrate to the United Kingdom, Canada, and United States in higher amounts and away from other European destinations (such as France and Spain).

Table 2.2 shows the Model results. Model 1 demonstrates a quadratic relationship with GDP per capita (quadratic term 0.19, 95% CI 0.03, 0.35), which does not reproduce in the gravity model (Model 2: 0.09, 95% CI -0.15, 0.39). The linear gravity model demonstrates a general decline in physician migration with increasing GDP per capita (Model 3: -0.76% per 1% increase in GDP, 95% CI -1.25%, -0.28%). When decomposed by region of the world, there is a negative relationship of varying magnitudes in Central Asia, East Asia, North America, and South Asia, a positive relationship with GDP per capita in EU European countries, and no significant linear relationship with GDP per capita and physician migration in the non-EU European Countries, the Middle East and North Africa (MENA), and sub-Saharan Africa.

Sensitivity analyses show that quadratic gravity models suggest a potential quadratic relationship with GDP for MENA countries and Latin America (eTable 2.1). When variables are lagged up to 5 years, the origin country GDP per capita effects become more positive and statistically significant for non-EU European countries (eTable 2.2). Finally, outside of Asia changing fixed effects show varying effect estimates, including a positive and statistically significant relationship with GDP in non-EU European countries with destination-year + origin fixed effects and a negative relationship in sub-Saharan Africa with additive origin+ destination + year fixed effects.

Mechanisms

The relationship between GDP and total physician migrant counts by region appears to be similar to annual migration rates and GDP (eFigure 2.1). There does not appear to be higher migration rates for countries with relatively low healthcare spending and high public sector dependence (i.e., circles are not larger in the top left corner of eFigure 2.2). There does not appear to be any increased relationship between origin country GDP and specialization rates of emigrated physicians in the UK, although broadly speaking, poorer regions of the world (South Asian and sub-Saharan African) do specialize less than other parts of the world (eFigure 2.3). Only South Asia, MENA and sub-Saharan Africa appear to have higher percentages of women among emigrated physicians in the UK with increasing GDP (eFigure 2.4). The concentration of medical schools of emigrated physicians in the UK downtrended (i.e., physicians came from a broader array of schools) as origin countries became wealthier, except for MENA countries.

Figure 2. 2: GDP per capita and Physician Migration Rates

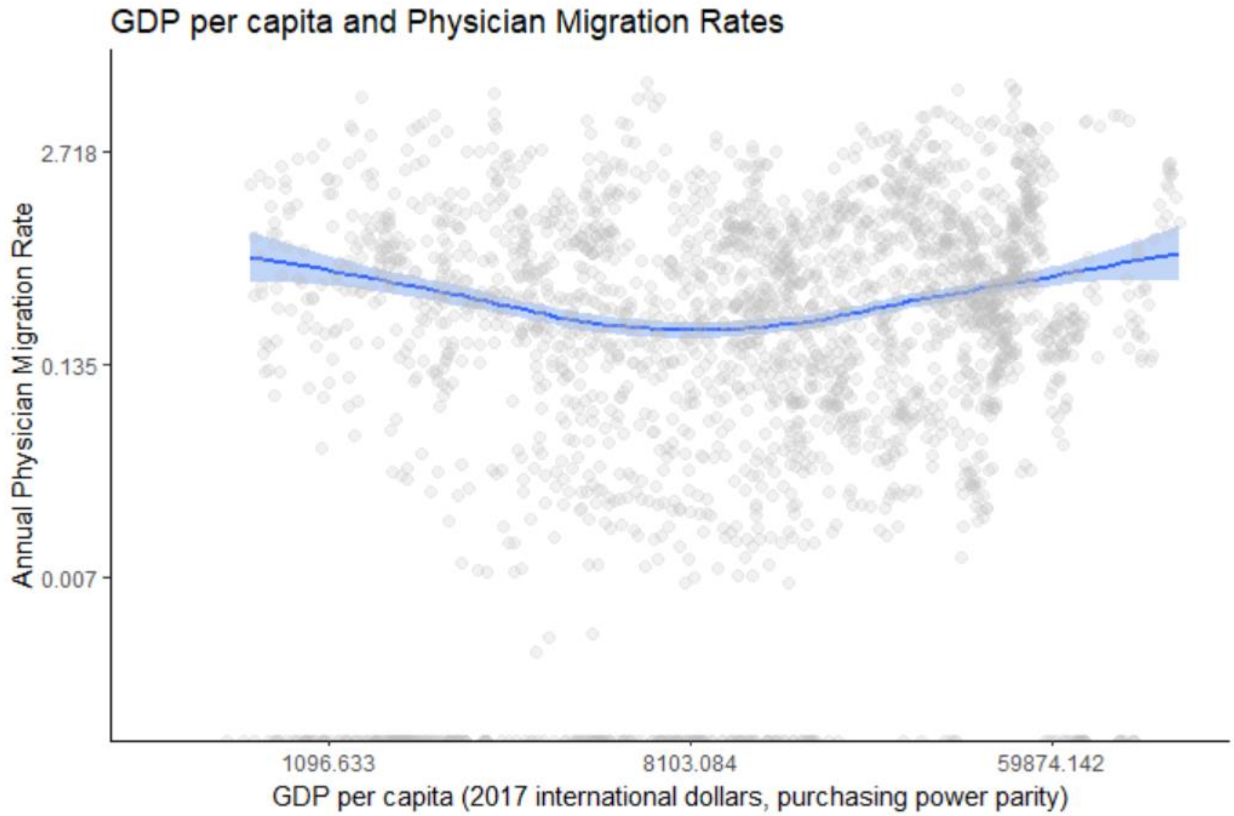


Figure 2. 3: Annual Physician Migration Rates, by Origin Region

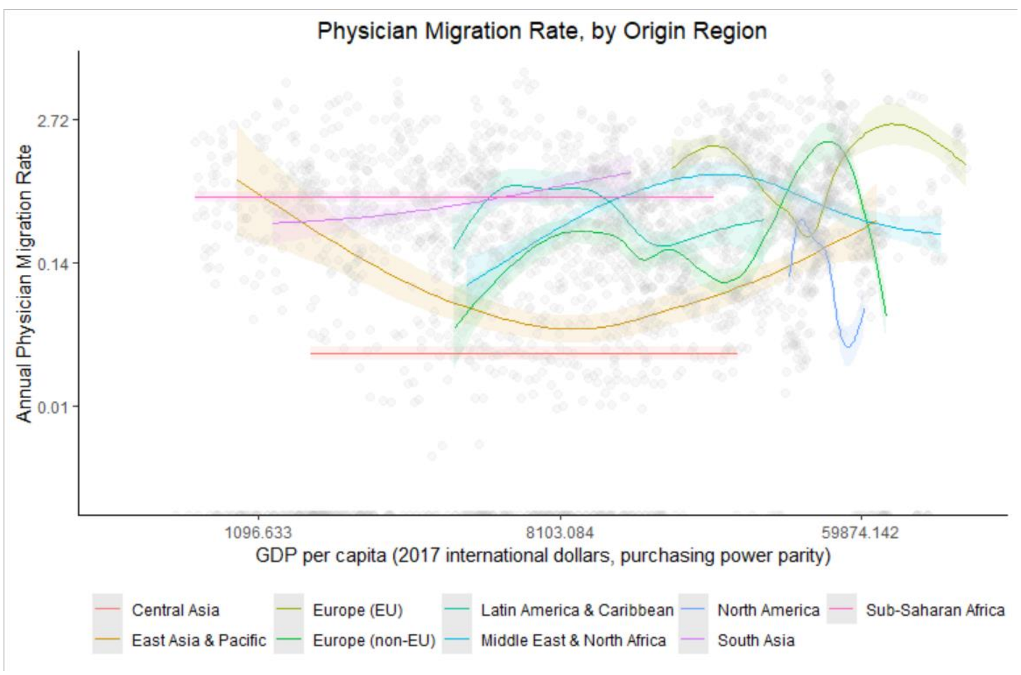


Figure 2. 4 : East Asia/Pacific Migration Rate, by Country

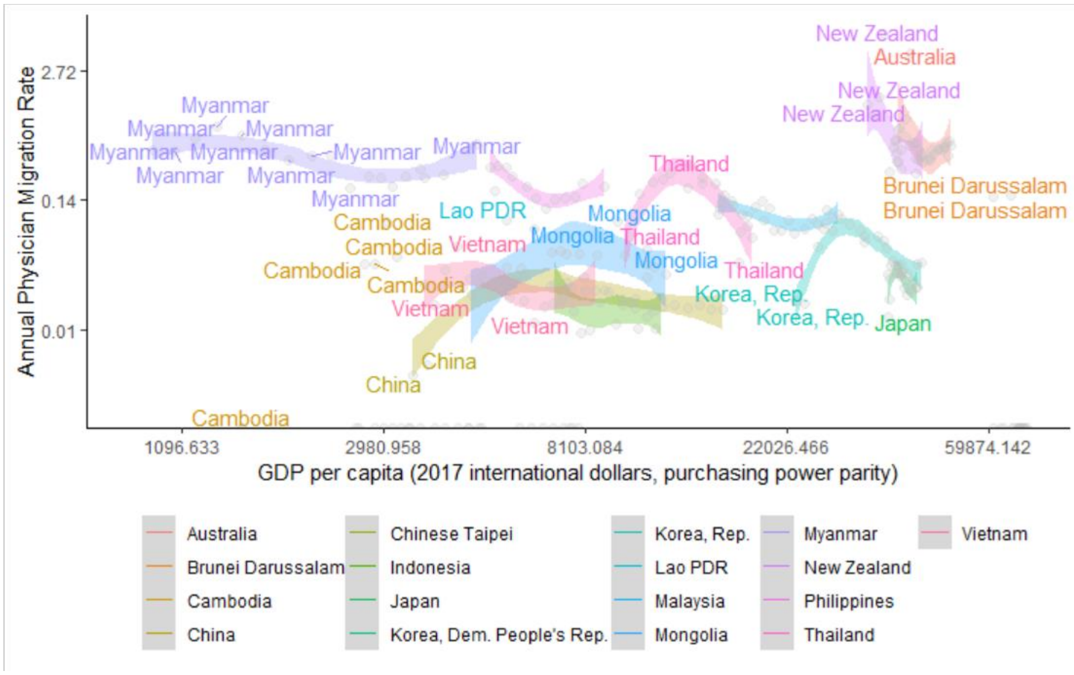


Figure 2. 5: Europe and Central Asia Emigration Rate, by Country

Figure 2. 6: South Asia Emigration rate, by country:

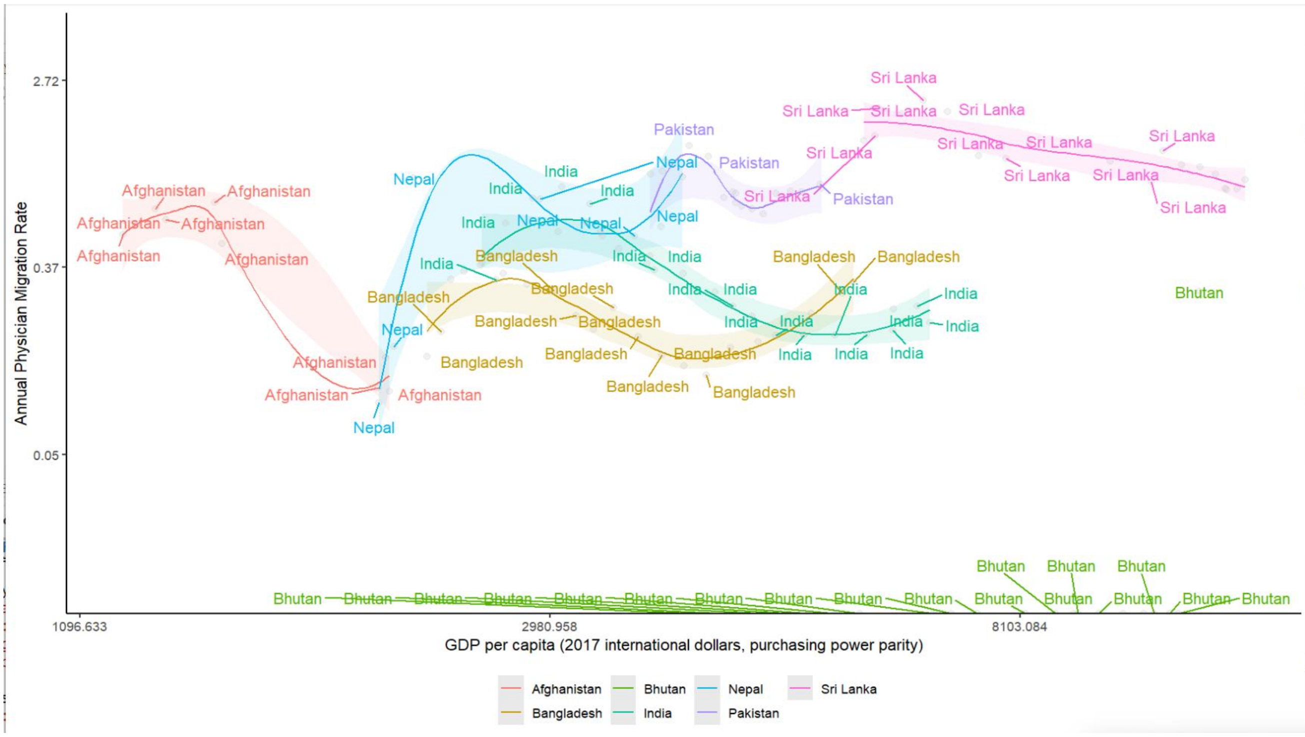


Figure 2. 7: Middle East and North Africa Emigration Rate, by Country:

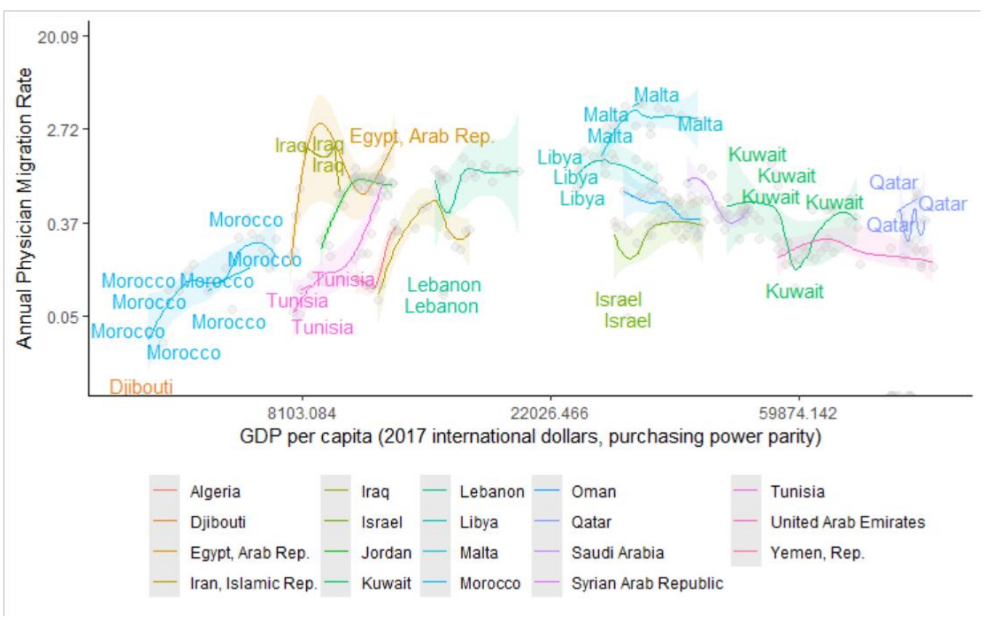


Figure 2. 8: Sub-Saharan Africa Emigration Rate, By Country:

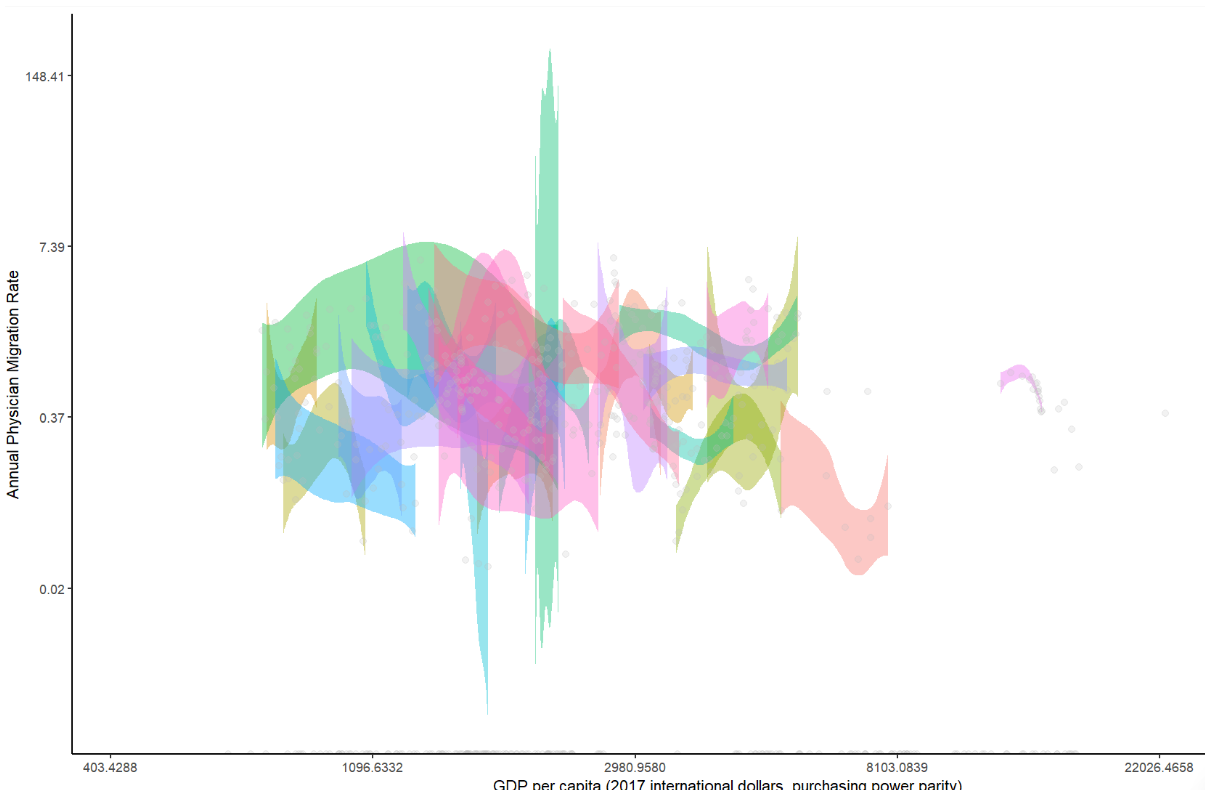


Figure 2. 9 Latin America Emigration Rate, By Country:

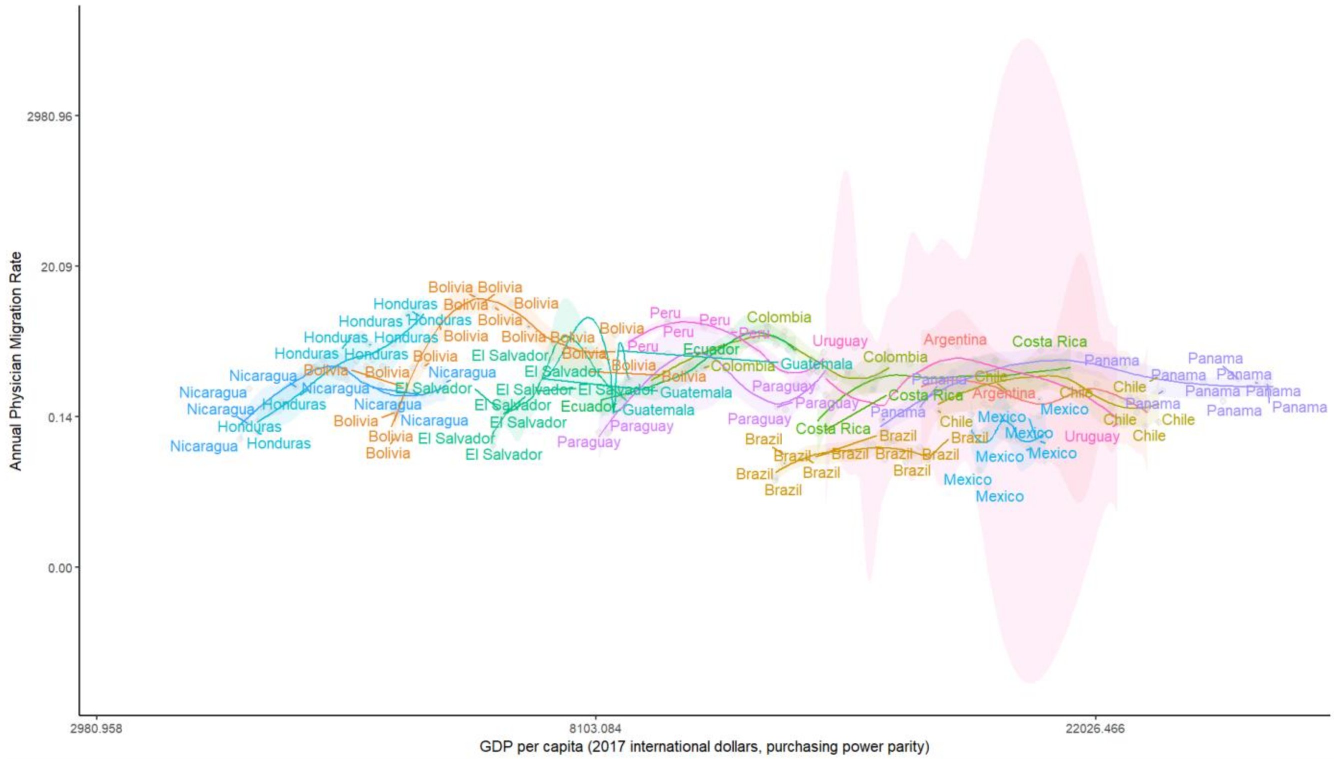


Figure 2. 10: Annual Physician Migration Rates, by Major Destination Country

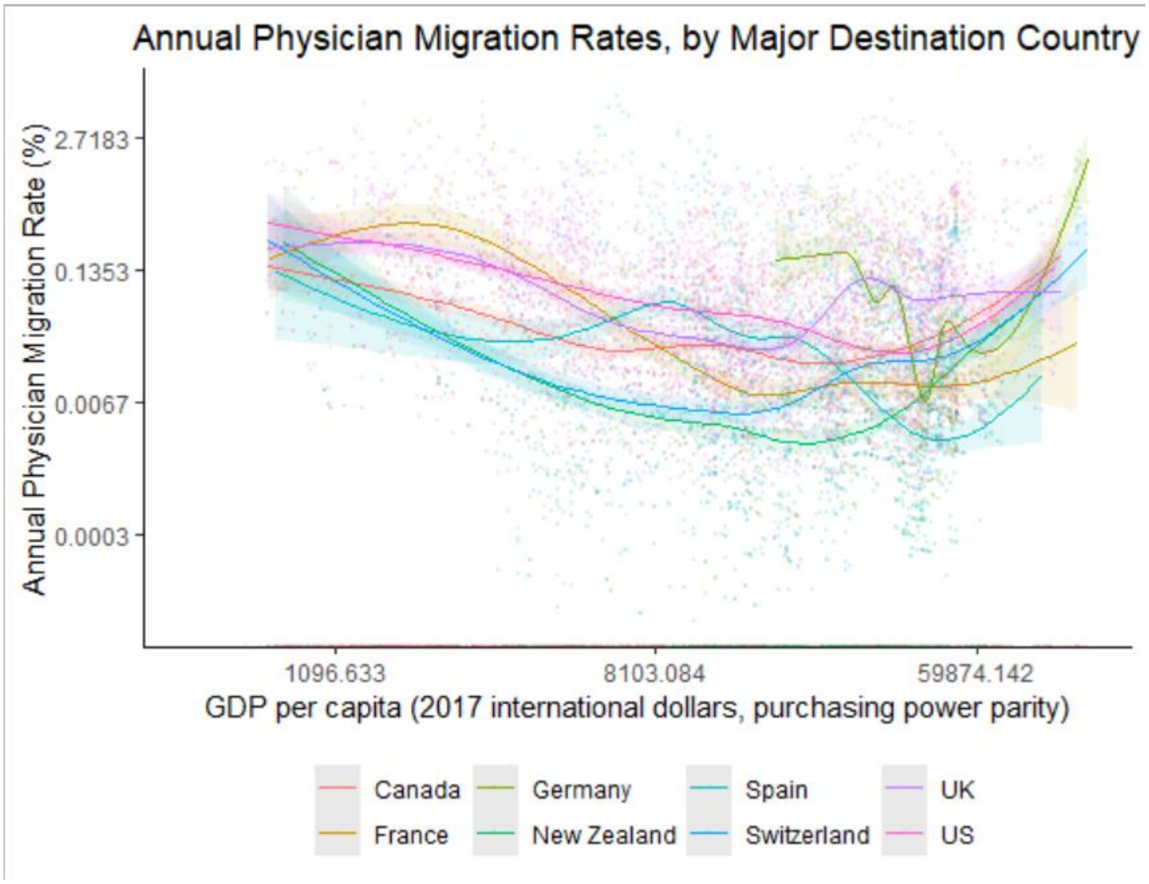
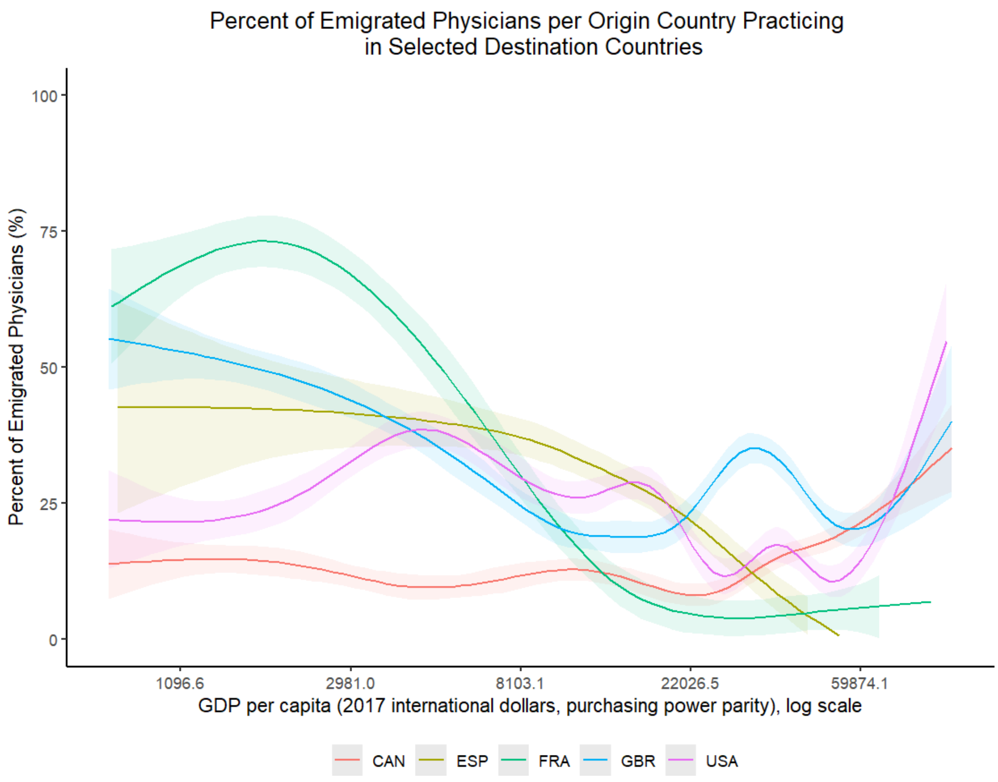


Figure 2. 11: Percent of Emigrated Physicians per Origin Country Practicing in Selected Destination Countries



Discussion

This study analysis demonstrates that the relationship between GDP per capita and physician migration is not uniformly negative, as might be suggested by prior observations. Rather, there appears to be heterogeneity between different regions, with regions like East and South Asia and North America having a negative relationship between GDP and physician migration, non-EU Europe having a broadly positive relationship, the Middle East and North Africa (MENA) having a quadratic relationship, and Latin America and sub-Saharan African showing income-resistance to migration in descriptive results. Within statistical models controlling for other origin and destination country factors, this relationship appears to replicate for East and South Asia, the EU, and North America and the Middle East and North Africa, becomes negative within Central Asia and Latin America, and is not statistically significant in non-EU European countries and sub-Saharan Africa. However, with increasing lags this effect becomes statistically significant and positive in non-EU European countries, demonstrating potential delayed effects of GDP on migration in Europe (e.g., due training delays among potential migrants). Changing the level of fixed effects (while maintaining a one-year lag) seems to produce broadly similar effects across Asia but importantly produces a positive statistically significant result in non-EU Europe (for destination-year interactive fixed effects). Otherwise, this relationship does not seem to be fully explained by origin country physician density, secular temporal changes, or health sector spending levels. Descriptive findings do not suggest that these findings are solely due to changes in migrant gender or specialization rates at destination or changes in concentration of "feeder" medical schools. eTable 1 demonstrates similar emigrated stock and flow trends, suggesting that changes are not related to short-term circular migration. Finally, observations also indicate that destination countries might also shift as countries become wealthier, with richer countries migrating to the United Kingdom and Canada in higher amounts, particularly from Europe.

As described in other literature, the mobility transition might predict monotonic declines in skilled emigration. In this context, however, the lack of homogenous changes with GDP per capita across regions might underline the importance of regional contextualization over any one unifying theory of migration. For example, Balkan and Eastern European countries might have increased departure as national GDP rose and countries transitioned into post-communist settings, phenomena that forced Albania to pose strict emigration restrictions[92,93]. There is some evidence of Gulf countries supporting emigration as a means of physician training as well[94]. One the other hand, GDP per capita changes might indicate better unmeasured living and working conditions, which have led to a decline in emigration in regions South and East Asia.

Another explanation for this finding is that these changes are destination country driven, at least in part. In all our gravity models, destination country GDP had significant effects, and several studies using gravity models focused on destination country factors has suggested the importance of factors such as local health benefits, low destination-country physician density, and changes in migration policies[78,79,95,96]. Also noted was the observation that destination country choices of emigrated physicians change as origin countries become wealthier, becoming more concentrated within English-speaking destinations. The effect of destination country factors is more difficult to capture when migrant destinations are also shifting due to the fixed effects structure of the model. However, it is possible that simultaneously there might be increasing origin country wealth, changes in destination country factors (e.g, more or less favorable migration policies to wealthier countries), and changes in migrant assortment to more favorable destination countries that lead to paradoxical increases physician migration for some regions and declines in others. For certain MENA and non-EU European countries, this might lead to increased migration to OECD countries (since the cost of migration is low and better overcome in wealthier origin settings), while for other regions of the world it has no impact or might be associated with a decline in migration (either due to increased retention or alterative destinations such as regional or Gulf countries). Shifts towards more regional related migration with more wealth might all partially explain why only non-EU European migration increases with GDP, as most OECD destinations are European.

These findings complicate projections of physician migration and might demand closer attention be paid to conditions other than national income and healthcare spending in predicting and managing. While in some settings physician migration might decline as the country became wealthier, it is also possible within another scenario, physician migration might increase or not change at all. Special consideration should be made to non-EU countries in Europe which is the only region that showed a potentially positive relationship between migration GDP per capita, and sub-Saharan Africa and MENA countries, where there was broadly no (or potentially higher order) relationship between GDP and migration. While various work has focused on physician migration crises within Africa and South Asia, physician migration has become a geographically widespread problem, compelling governmental responses. While Europe does have a higher baseline concentration of physicians, the impacts to Europe are likely to become more severe as non-EU countries become wealthier, unlike other parts of the world.

Limitations

Limitations include that lack of physician registry data from Australia (which does not such report data to the OECD) and from Gulf Countries. Also, individual level data was not attainable from outside the United Kingdom, and this paper does not analyze data since the 2019, including the COVID pandemic.

Conclusion

The relationship between GDP and physician emigration is heterogenous, with a generally negative association in most regions, no relationship in sub-Saharan Africa, a quadratic relationship in the Middle East and North Africa, and a lagged positive relationship in non-EU European countries.

Supplement

eTable 2. 1: Destination Countries

Austria
Belgium
Canada
Chile
Czech Republic
Estonia
Finland
France
Greece
Hungary
Ireland
Israel
Latvia
Lithuania
Netherlands
New Zealand
Norway
Poland
Portugal
Slovenia
Sweden
Switzerland
Turkey
United Kingdom
United States

eTable 2. 2: Lagged Results (origin-destination + year fixed effects, clustered at origin level)

	Year 1	Year 2	Year 3	Year 4	Year 5
Ln(Origin GDP)* Central Asia $_{t-1}$‡	-1.04 (-1.59, -0.50)***	-0.62 (-1.39, 0.16)	-0.14 (-0.92, 0.63)	-0.10 (-0.89, 0.69)	0.17 (-0.64, 0.98)
Ln(Origin GDP)*EU $_{t-1}$‡	-1.06 (-1.51, -0.62)***	-0.54 (-0.93, -0.15)**	-0.26 (-0.63, 0.10)	-0.07 (-0.37, 0.24)	0.00 (-0.23, 0.23)
Ln(Origin GDP)* East Asia & Pacific $_{t-1}$‡	-0.70 (-1.17, -0.23)**	-0.67 (-1.17, -0.17)**	-0.62 (-1.11, -0.12)*	-0.38 (-0.67, -0.10)**	-0.37 (-0.70, -0.05)*
Ln(Origin GDP) *Europe (non-EU) $_{t-1}$‡	-0.07 (-0.74, 0.60)	0.37 (-0.35, 1.10)	0.79 (-0.02, 1.60)	1.02 (0.16, 1.88)*	1.13 (0.34, 1.93)**
Ln(Origin GDP) *Latin America $_{t-1}$‡	-1.95 (-3.27, -0.63)**	-1.87 (-3.09, -0.65)**	-1.95 (-3.33, -0.57)**	-1.88 (-3.61, -0.14)*	-1.52 (-3.38, 0.33)
Ln(Origin GDP) *Middle East and North Africa $_{t-1}$‡	0.72 (-0.98, 2.42)	0.75 (-0.69, 2.18)	0.53 (-0.68, 1.74)	-0.17 (-1.05, 0.71)	-0.21 (-1.05, 0.64)
Ln(Origin GDP) *North America $_{t-1}$‡	-2.51 (-3.62, -1.41)***	-2.33 (-3.43, -1.23)***	-1.94 (-2.99, -0.88)***	-1.98 (-2.96, -1.01)***	-1.92 (-2.89, -0.94)***
Ln(Origin GDP) * South Asia $_{t-1}$‡	-1.40 (-1.86, -0.94)***	-1.02 (-1.48, -0.57)***	-0.94 (-1.38, -0.49)***	-0.90 (-1.35, -0.45)***	-0.84 (-1.30, -0.39)***
Colonial Link†	---	---	---	---	---
Common Language†	---	---	---	---	---
Ln(Origin GDP) * Sub-Saharan Africa$_{t-1}$‡	-0.37 (-0.87, 0.13)	0.00 (-0.53, 0.53)	0.35 (-0.22, 0.92)	0.48 (-0.11, 1.07)	0.66 (-0.03, 1.34)
Ln(Destination GDP)$_{t-1}$‡	1.86 (0.77, 2.95)**	1.57 (0.50, 2.64)**	1.18 (0.02, 2.33)*	0.55 (-0.67, 1.78)	-0.15 (-1.34, 1.05)
Joint Schengen$_{t-1}$†	0.53 (0.28, 0.78)***	0.53 (0.30, 0.76)***	0.54 (0.31, 0.78)***	0.50 (0.23, 0.77)***	0.39 (0.15, 0.63)**
Ln(Diaspora Size)$_{t-5}$‡	0.12 (-0.04, 0.28)	0.04 (-0.16, 0.24)	-0.02 (-0.23, 0.19)	-0.11 (-0.33, 0.11)	-0.16 (-0.36, 0.05)
Ln(Physicians per Capita)$_{o, t-5}$‡	-0.17 (-0.41, 0.08)	-0.17 (-0.39, 0.05)	-0.10 (-0.31, 0.10)	0.04 (-0.16, 0.24)	0.06 (-0.17, 0.29)
Ln(% of GDP on health spending)‡	-0.20 (-0.71, 0.31)	-0.01 (-0.46, 0.44)	0.13 (-0.36, 0.62)	0.28 (-0.32, 0.88)	0.43 (-0.20, 1.06)

*p<0.05, **p<0.01, ***p<0.001

‡Elasticities, i.e., % change in physician migration for every 1% change in predictor in linear models

†Can be converted to semi-elasticities. i.e, with conversion ($e^{\text{coefficient}}$-1)*100 can be interpreted as % change for one-level change in predictor.

eTable 2. 3: Regional coefficients under varying fixed effect approaches

	Model 1	Model 2	Model 3
Ln(Origin GDP)* Central Asia $_{t-1}$‡	-1.04 (-1.59, -0.50)***	-0.76 (-1.50, -0.02)*	-1.45 (-1.98, -0.92)***
Ln(Origin GDP)*EU $_{t-1}$‡	-1.06 (-1.51, -0.62)***	0.21 (-0.05, 0.47)	-1.11 (-1.71, -0.51)***
Ln(Origin GDP)* East Asia & Pacific $_{t-1}$‡	-0.70 (-1.17, -0.23)**	-0.41 (-0.79, -0.02)*	-0.80 (-1.34, -0.26)**
Ln(Origin GDP) *Europe (non-EU) $_{t-1}$‡	-0.07 (-0.74, 0.60)	0.95 (0.14, 1.75)*	-0.22 (-0.88, 0.43)
Ln(Origin GDP) *Latin America $_{t-1}$‡	-1.95 (-3.27, -0.63)**	0.22 (-1.93, 2.37)	-0.77 (-2.54, 1.00)
Ln(Origin GDP) *Middle East and North Africa $_{t-1}$‡	0.72 (-0.98, 2.42)	-0.05 (-1.26, 1.15)	0.87 (-0.99, 2.72)
Ln(Origin GDP) *North America $_{t-1}$‡	-2.51 (-3.62, -1.41)***	0.10 (-1.31, 1.51)	-1.50 (-2.83, -0.18)*
Ln(Origin GDP) * South Asia $_{t-1}$‡	-1.40 (-1.86, -0.94)***	-0.91 (-1.48, -0.35)**	-1.60 (-2.14, -1.06)***
Ln(Origin GDP) * Sub-Saharan Africa$_{t-1}$‡	-0.37 (-0.87, 0.13)	0.50 (-0.30, 1.30)	-0.74 (-1.28, -0.20)**
Ln(Destination GDP)$_{t-1}$‡	1.86 (0.77, 2.95)**	--	2.64 (1.56, 3.72)***
Colonial Link†	-------	-0.54 (-1.07, -0.01)*	-0.51 (-1.08, 0.07)
Common Language†	-------	1.03 (0.58, 1.48)***	0.97 (0.55, 1.39)***
Joint Schengen$_{t-1}$†	0.53 (0.28, 0.78)***	0.58 (0.00, 1.17)	0.73 (0.26, 1.20)**
Ln(Diaspora Size)$_{t-5}$‡	0.12 (-0.04, 0.28)	0.68 (0.54, 0.81)***	0.68 (0.54, 0.81)***
Ln(Physicians per Capita)$_{o, t-5}$‡	-0.17 (-0.41, 0.08)	0.13 (-0.22, 0.48)	-0.11 (-0.41, 0.20)
Ln(% of GDP on health spending)‡	-0.20 (-0.71, 0.31)	0.65 (-0.03, 1.33)	-0.19 (-0.67, 0.28)
Fixed effects	Origin-destination + year	Origin destination-year	origin+ destination+ year
Clustering	Origin Country	Origin Country	Origin Country

*p<0.05, **p<0.01, ***p<0.001

‡Elasticities, i.e., % change in physician migration for every 1% change in predictor in linear models

†Can be converted to semi-elasticities. i.e, with conversion ($e^{coefficient}$-1)*100 can be interpreted as % change for one-level change in predictor.

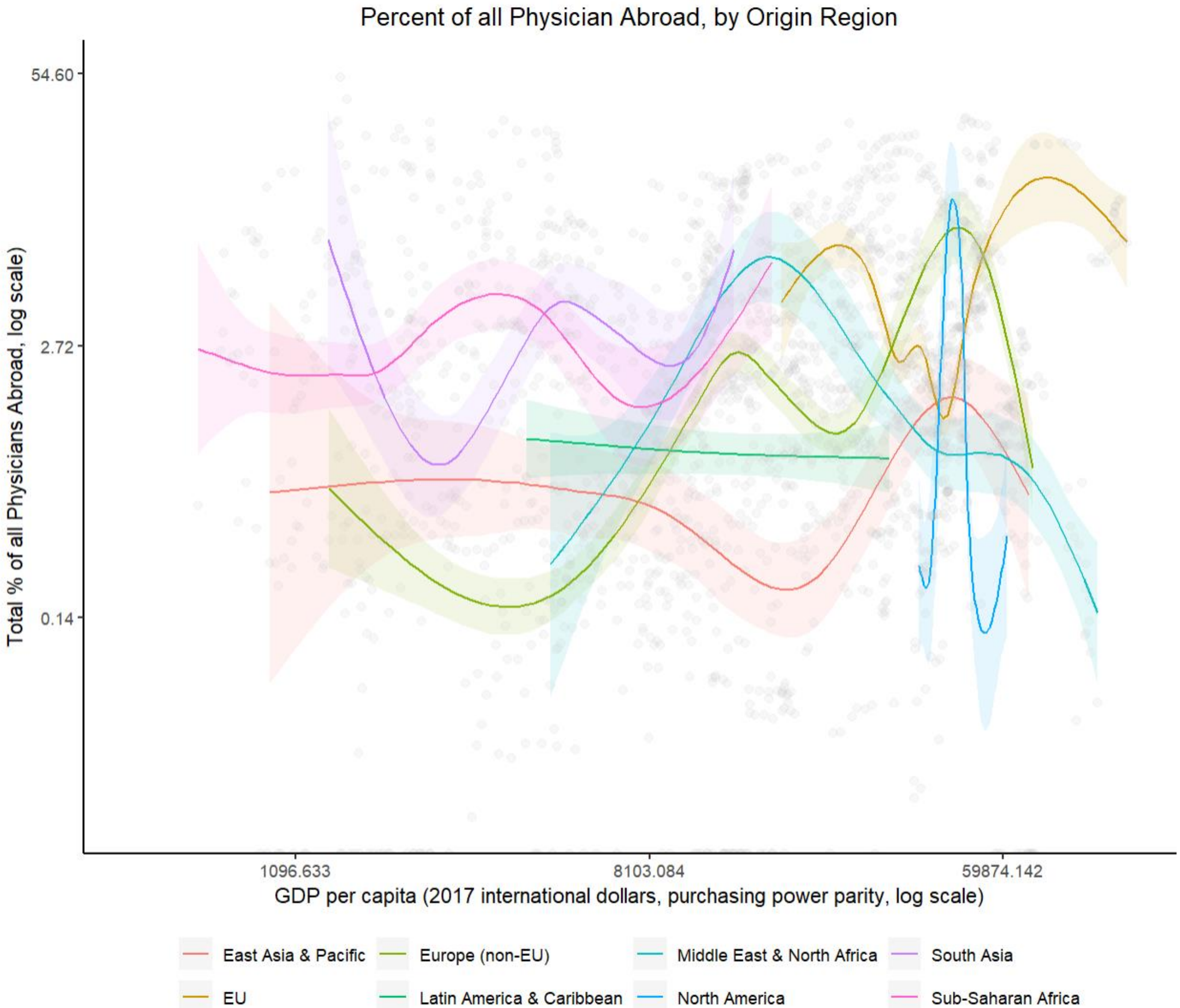
eTable 2. 4: Expanded Regional Interactions

	OLS Quadratic	OLS Linear	Gravity Quadratic	Gravity Linear
Ln(Origin GDP)^2* Central Asia $_{t-1}$‡	0.16 (-0.30, 0.61)		-0.87 (-2.56, -1.18)*	
Ln(Origin GDP)^2*EU $_{t-1}$‡	-1.25 (-2.31, -0.19)*		0.04 (-1.01, -0.90)	
Ln(Origin GDP)^2* East Asia & Pacific $_{t-1}$‡	-0.24 (-0.54, 0.07)		-0.63 (-2.09, -1.18)**	
Ln(Origin GDP)^2 *Europe (non-EU) $_{t-1}$‡	-0.13 (-0.81, 0.54)		0.06 (-1.00, -0.89)	
Ln(Origin GDP)^2 *Latin America $_{t-1}$‡	-1.11 (-2.43, 0.22)		-1.81 (-4.21, -1.41)*	
Ln(Origin GDP)^2 *Middle East and North Africa $_{t-1}$‡	-0.46 (-0.93, 0.02)		0.06 (-1.00, -0.88)*	
Ln(Origin GDP)^2 *North America $_{t-1}$‡	-10.83 (-18.44, -3.22)**			
Ln(Origin GDP)^2 * South Asia $_{t-1}$‡	0.36 (-0.21, 0.92)		-1.33 (-2.77, -1.89)***	
Ln(Origin GDP)^2 * Sub-Saharan Africa$_{t-1}$‡	0.20 (-0.62, 1.02)		-0.21 (-1.81, -0.61)	
Ln(Origin GDP)* Central Asia $_{t-1}$‡	-4.10 (-12.65, 4.46)	-1.32 (-2.15, -0.50)**		-1.04 (-1.59, -0.50)***
Ln(Origin GDP)*EU $_{t-1}$‡	23.97 (2.74, 45.19)*	-1.55 (-1.91, -1.19)***	-0.98 (-3.21, -0.74)	-1.06 (-1.51, -0.62)***
Ln(Origin GDP)* East Asia & Pacific $_{t-1}$‡	2.94 (-2.30, 8.18)	-1.15 (-1.67, -0.63)***		-0.70 (-1.17, -0.23)**
Ln(Origin GDP) *Europe (non-EU) $_{t-1}$‡	1.83 (-10.94, 14.60)	-0.65 (-1.36, 0.06)	-0.09 (-1.82, -0.36)	-0.07 (-0.74, 0.60)
Ln(Origin GDP) *Latin America $_{t-1}$‡	20.98 (-4.63, 46.60)	0.09 (-1.00, 1.18)		-1.95 (-3.27, -0.63)**
Ln(Origin GDP) *Middle East and North Africa $_{t-1}$‡	9.07 (-0.42, 18.56)	0.15 (-0.95, 1.25)	0.93 (-1.99, 1.86)	0.72 (-0.98, 2.42)
Ln(Origin GDP) *North America $_{t-1}$‡	226.35 (64.11, 388.60)**	-4.48 (-5.56, -3.39)***		-2.51 (-3.62, -1.41)***
Ln(Origin GDP) * South Asia $_{t-1}$‡	-7.80 (-17.59, 1.99)	-1.72 (-2.45, -0.99)***		-1.40 (-1.86, -0.94)***
Ln(Origin GDP) * Sub-Saharan Africa$_{t-1}$‡	-4.87 (-17.73, 8.00)	-1.71 (-2.59, -0.83)***		-0.37 (-0.87, 0.13)
Ln(Origin GDP)* Central Asia $_{t-1}$‡				
Ln(% of GDP on health spending)‡	-0.18 (-0.58, 0.23)	-0.09 (-0.47, 0.30)	-0.17 (-1.64, -0.71)	-0.20 (-0.71, 0.31)
ln_physiciansper1000peoples_i				
Ln(Physicians per Capita)$_{o, t-5}$‡	-0.15 (-0.45, 0.16)	-0.21 (-0.51, 0.09)	-0.15 (-1.41, -0.88)	-0.17 (-0.41, 0.08)
Ln(Destination GDP)$_{t-1}$‡			1.80 (-0.22, 1.83)**	1.86 (0.77, 2.95)**
Joint Schengen$_{t-1}$†			0.56 (-0.68, -0.20)***	0.53 (0.28, 0.78)***
Ln(Diaspora Size)$_{t-5}$‡			0.09 (-1.12, -0.71)	0.12 (-0.04, 0.28)

*p<0.05, **p<0.01, ***p<0.001

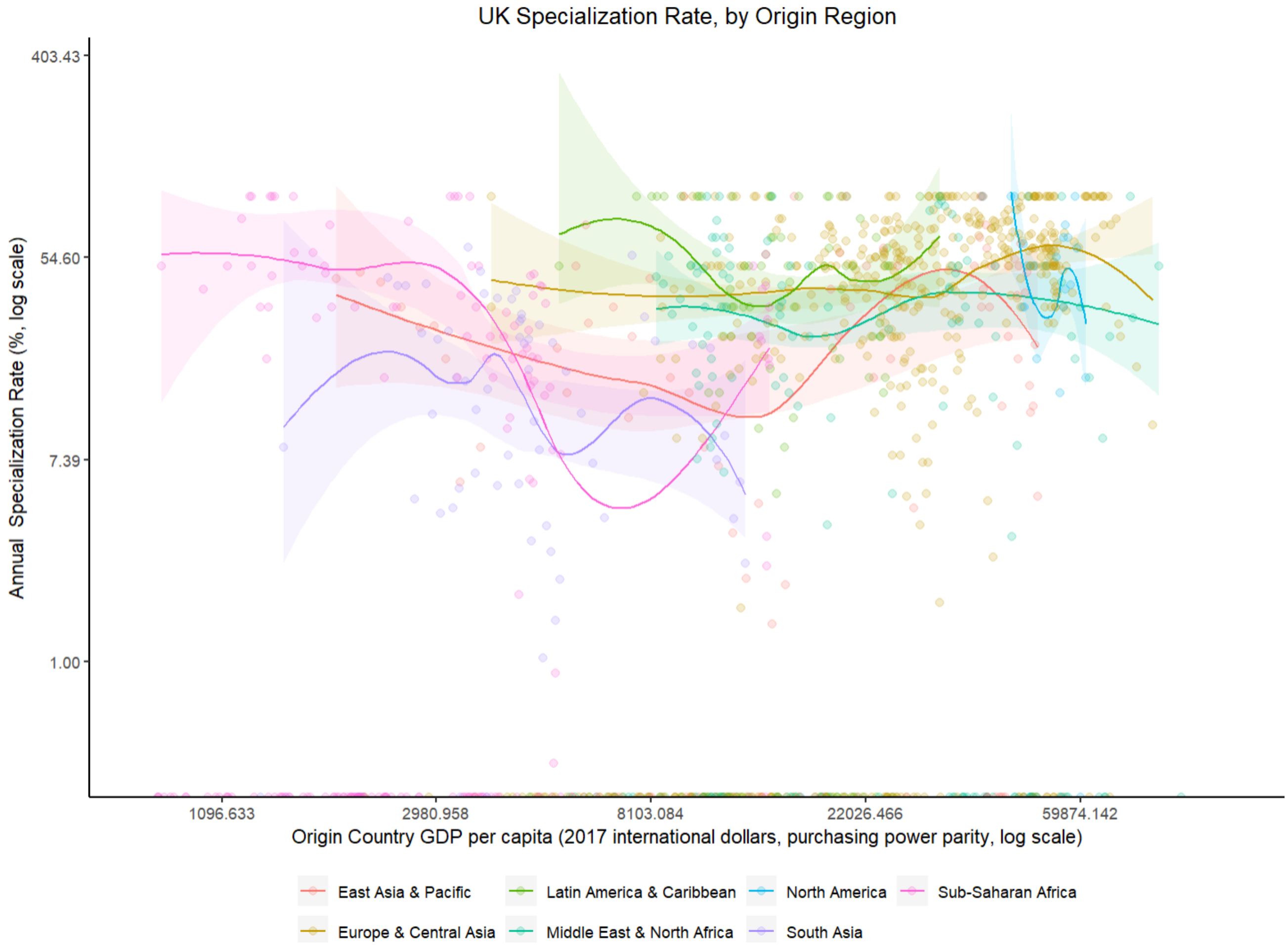
‡Elasticities, i.e., % change in physician migration for every 1% change in predictor in linear models; †Can be converted to semi-elasticities. i.e, with conversion ($e^{\text{coefficient}}$-1)*100 can be interpreted as % change for one-level change in predictor.

eFigure 2. 1: Physician migrant stocks and GDP per capita, by origin region

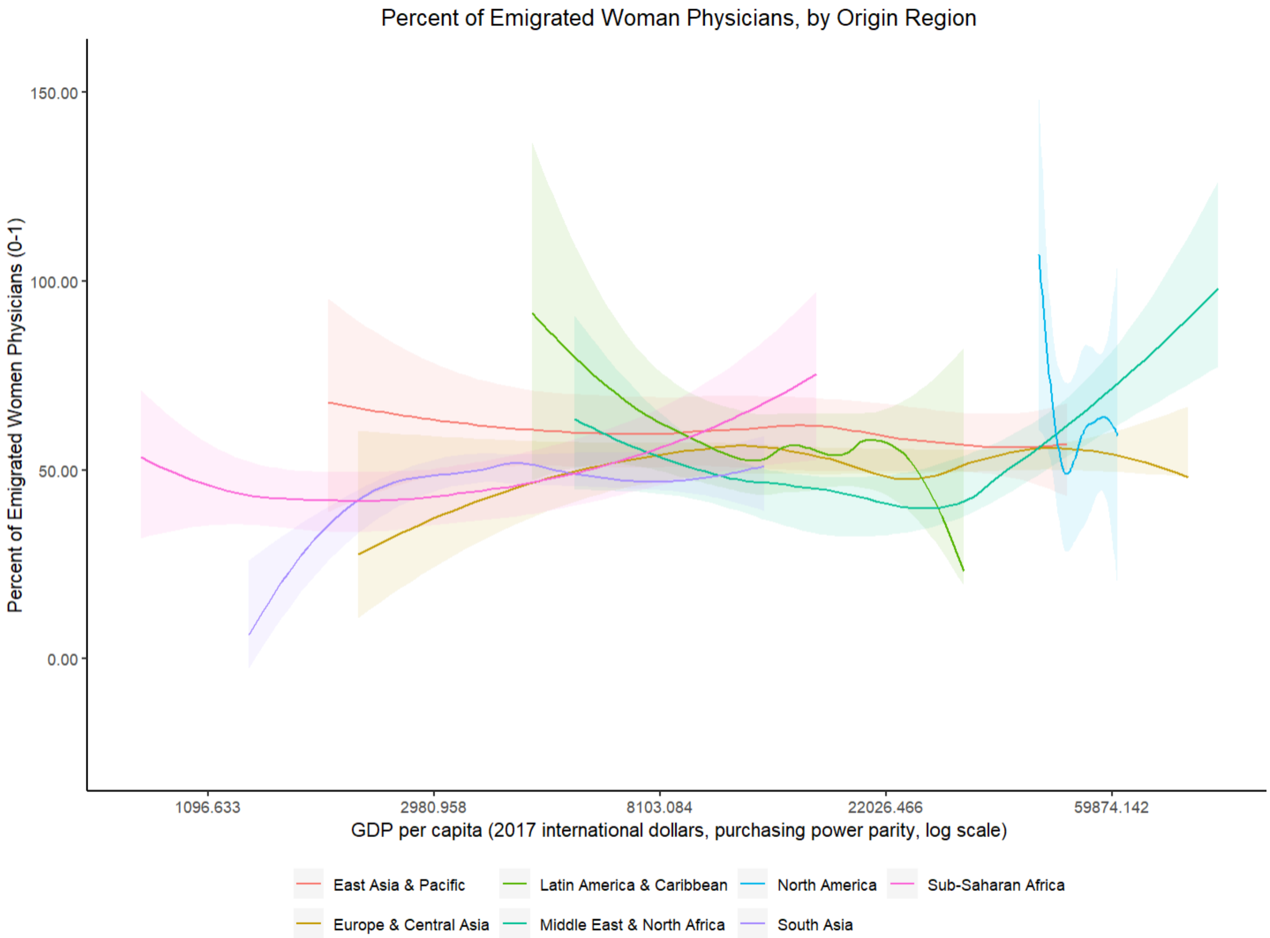


eFigure 2. 2: Physician Migration Rates, by Origin Country Public Spending Dependence and Domestic Total Health Spending

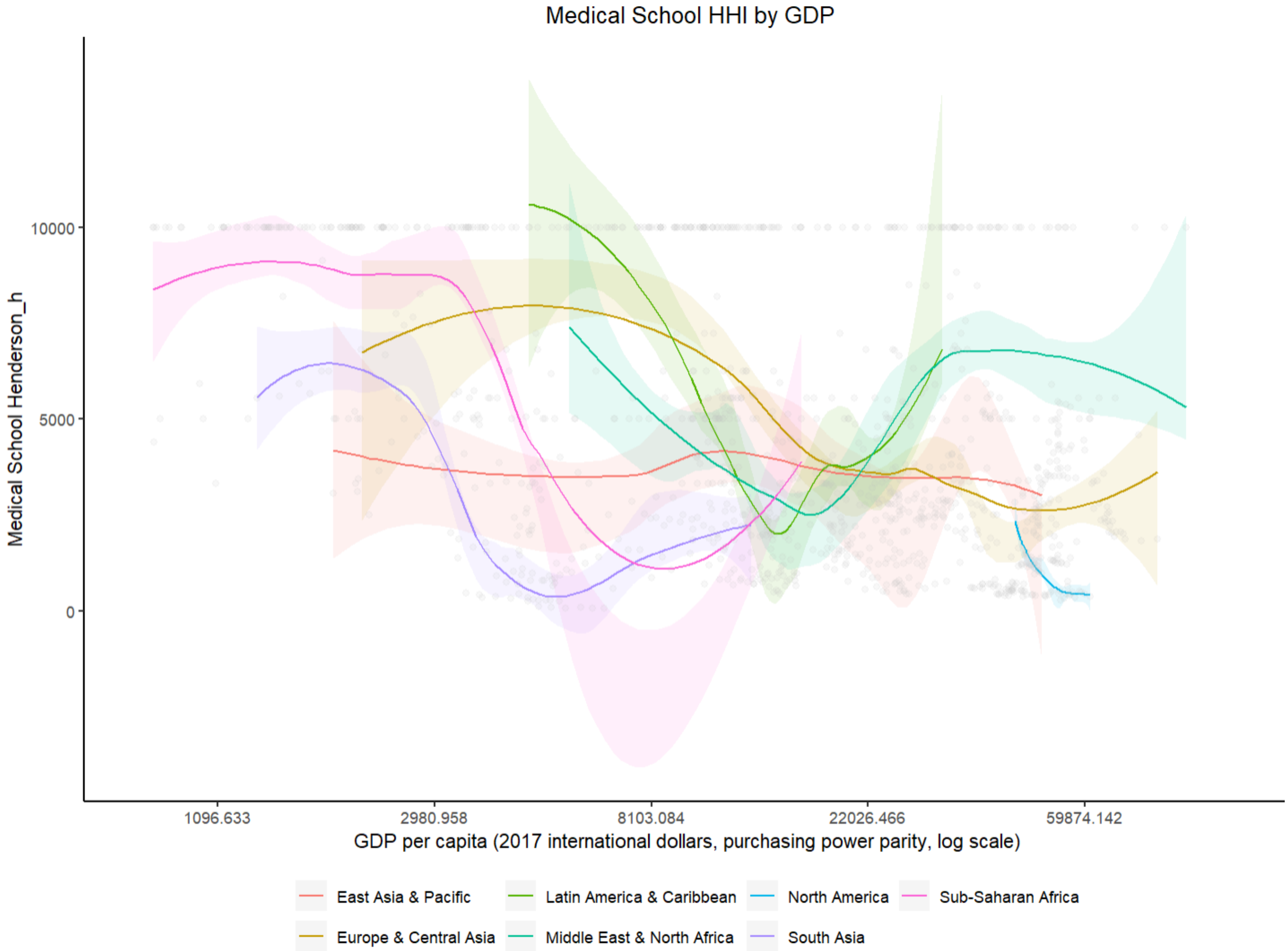
eFigure 2. 3: Physician Migration Rates, by Origin Country Public Spending Dependence and Domestic Total Health Spending



eFigure 2. 4: Women as Percent of Emigrated Physicians by Origin Region



eFigure 2. 5: Medical School Herfindahl-Hirschman Index and GDP, by origin region



Chapter 3: At the Nexus of Race and Legal Status: Health Outcomes among Black Undocumented Immigrants

Abstract

Introduction: Undocumented immigrants face several barriers to achieving health and health access. Black undocumented immigrants face barriers not only due to their legal status but also due to structural racism in American society. However, there is little known about the health profiles and health risks of Black undocumented immigrants, and there is no analysis using nationally representative data. Thus, this study analyzes Black undocumented immigrants' health across 3 domains: health care access, mental health, and sleep.

Methods: This data uses nationally representative data from the National Health Interview Survey (NHIS) from 1999 to 2018 to examine healthcare access and healthcare outcomes along two dimensions legal status (undocumented, documented, naturalized citizen and US-Born citizen, among Black individuals) and race (race and ethnicity strata among undocumented immigrants). We analyze five outcomes: health insurance access, clinician visits in the past two years and overnight hospitalizations in the past year (for individuals over 40 years), severe mental distress, and hours of sleep. Across legal status and race strata non-Hispanic White US-Born citizens (NHWC) were used as the referent category.

Results: Among Black individuals across legal strata, Black undocumented immigrants had higher odds of being uninsured (OR 7.1, 95% CI 6.3, 8.0) and of having no clinician visits (OR 2.5, 95% CI 2.1, 3.1). Black US-Born Citizens, however, had higher odds of being hospitalized (OR 1.1 95% CI 1.1, 1.2) and of severe mental distress (OR 0.9, 95% CI 0.8, 0.9) and Black Naturalized Citizens had less hours of sleep (-0.2, 95% CI -0.3, -0.1). Most undocumented groups had higher odds of uninsurance compared to NHWC, with higher odds for Hispanic

subgroups. Hispanic Asian (OR 4.5, 95% CI 2.1, 9.5) and Hispanic Black (OR 4.2 95% CI 2.6, 6.8) respondents had higher odds of no recent clinician visits. Most groups had lower odds of hospitalizations, with lowest odds for non-Hispanic Black (OR 0.236, 95% CI 0.09, 0.6). There was no significant difference in severe mental distress, only non-Hispanic Black respondents had lower sleep than NHWC (-0.1 hours, 95% CI -0.2, -0.03).

Conclusion: The relationship between race, ethnicity, and legal status is complex. Legal status still has an important association with access to insurance and primary care; however, there are some important racial heterogeneities among undocumented immigrants, particularly in sleep and healthcare access.

Introduction

Black persons in the United States face unique challenges related to institutional and inter-personal anti-black racism. Among myriad societal and neighborhood disadvantages, they have lower SES than White individuals and are more likely than White individuals to have encounters with the criminal justice system. They are also more likely to be discriminated against in healthcare settings, with one compelling study showing that language in electronic medical records is more likely to use more negative terminology when describing Black vs white patients [97].

Research on outcomes of Black immigrants in the United States holds that they tend to have better self-reported health than their U.S.-born Black counterparts, a trend that holds for all immigrants compared to natives and which is termed the “immigrant health paradox”; this trend also holds for birth outcomes, mortality rates, self-reported hypertension, diabetes and obesity outcomes [28,29] (Further discussion of this is reported in the Conceptual Model). However, that research does not focus on undocumented immigrants, who experience vulnerability at the nexus of immigration status, race, ethnicity, and class. Legal exclusion from health insurance coverage (e.g. Medicaid in most US states, reinforced by labor market exclusion) and susceptibility to deportation regimes overlap, exacerbating inequities in health and healthcare access in this population.

These cumulative disadvantages may adversely affect Black undocumented immigrants, who make up 582,300 of the 11 million undocumented immigrants in the United States and 12% of Black immigrants[98]. These immigrants bear a heavy burden in large part due to interactions with the criminal justice system. Although they make up 5.4% of all undocumented immigrants, they make up 20.7% of all immigrants slated for deportation[99]. They are also very underrepresented for legal relief, with only 1% of DACA recipients being Black, and only 2-3% of African and Caribbean migrants as being eligible for DACA[100]. Black immigrants as a whole are uniquely marginalized, having the highest unemployment rate (12.5%) among all immigrants and lower wages than most immigrant groups, despite being among the most highly educated[101]. Despite these inequities, Black undocumented groups are often erased from broader conversations about immigration. While there are over 1,000 studies on undocumented immigrants on PubMed, the National Institutes of Health's health research registry, only four examine health among Black undocumented immigrants. Three articles, authored by Oluwatoyin Olukotun, demonstrate that patients have significant fear-based and financial barriers to care and as a result lack regular access to primary care and delay acute care seeking; that once they arrive to health care, they often receive insensitivity from providers and mistrust staff; and they are often isolated and financially vulnerable, with resultant stressors buttressed by faith-based coping mechanisms.[24–26] The other article, by Ross et al., details how stigma related to immigration and HIV status might impede access for undocumented African immigrants living with HIV in New York City. However, once connected to care, they have positive relationships with their care providers. [27]

There are no known studies examining the health of undocumented Black immigrants using national survey data. Furthermore, while there is some work comparing undocumented immigrants to same-race "authorized" immigrants among Asians and Latinos[102–105], there are no such studies for Black immigrant populations. Given the complex interplay of race, ethnicity and legal status in this population, further work to elucidate their ultimate health status is needed. This study seeks to understand health care access and health inequities for Black undocumented immigrants compared to Black foreign-born and US-born individuals, as well as compared to other undocumented immigrants.

Conceptual Model

The immigrant health paradox holds that immigrants to the US on average have higher self-reported health, most likely due to origin country selectivity into immigration; that is to say, individuals that immigrate to the United States have higher socioeconomic or health outcomes than other natives in their home country [28]. There are several caveats to this: first, studies show that there is significant heterogeneity in self-reported health status depending on countries of origins, with better health statuses for those who come from countries with higher GDP per capita, lower education levels, and high life expectancies at birth. (Among Black immigrants, individuals who come from countries with *higher* education levels and greater Black majorities have better health.)[28,106–108]. Second, immigrant health profiles tend to converge with native populations over time and across generations, according to multiple studies [28,109,110]. Third, local realities of cultural and structural racism might also complicate these trajectories[111]. Nonetheless, given the particularly malignant history and intergenerational effects of racism in the United States as well as the relative "selection" of Black migrants, it is possible that early life health risk exposure and potentially current health might have been better for Black undocumented immigrants compared to native-born Black Americans, although not necessarily native-born White Americans, as has been shown for studies of Black immigrants.

There are various ideas that provide support for the interplay of structural forces on health trajectories in this population. The first, critical race theory explains the stratification of race globally (including in the United States) might lead to marginalization of individuals not racialized as White[112]. The second, intersectionality identifies how an individual's separate social identities might predispose them to overlapping and intersecting systems of oppression in a society. In this case, undocumented Black immigrants are subject to marginalization due to anti-Blackness and anti-immigrant sentiment and policies, the latter of which might be heightened through language exclusion or legal exclusion due to their undocumented status [109,113]. The third, legal violence, explains how the state has merged the arms of criminal and immigration enforcement to impose oppressive conditions on undocumented immigrants, a process potentially exaggerated on undocumented Black immigrants.[114] Other forces, such as sexism, may further guide individual trajectories. As such, health risks might be *worse* for Black undocumented immigrants than other Black immigrants and undocumented immigrants of other races.

There are several models that have examined the relationship between structural racism, immigration status, and the outcomes to be studied. The first model (Figure 3.1) by Shi et Al. demonstrates how racial discrimination might predispose to poor sleep and mental health;

sensitivity to chronic pain might be similarly affected by this pathway along with undertreatment of existing pain. Key to the pathway is the exposure to discrimination and structural racism (as operationalized by income) as determinants and religion and substance use and abuse as mediators that might be protective or risk producing to mental distress. The second model (Figure 3.2) by Hacker et al. demonstrates how precarious legal status might predispose to decreased health care utilization. In that model, preexisting relationships with law enforcement, knowledge about ICE raids, and noncriminal surveillance and enforcement (from housing authorities or healthcare establishments) might combine to both produce mental distress and avoidance of healthcare.[115–117] These models are highly complementary insomuch as racial discrimination or structural racism are a common point of origin for these outcomes. At the same time, care must be taken when creating quantitative models, as many of the precursors (e.g., housing, occupation, law enforcement exposure) to poor outcomes are mediators, not confounders. The only true confounders are "exogenous" demographic variables, e.g., age, gender, ethnicity, years of arrival, time in the US, and region of residence. Measures are represented in Table 3.1.

Figure 3. 1: Structural Racism, Racial Discrimination and Mental distress/Poor Sleep

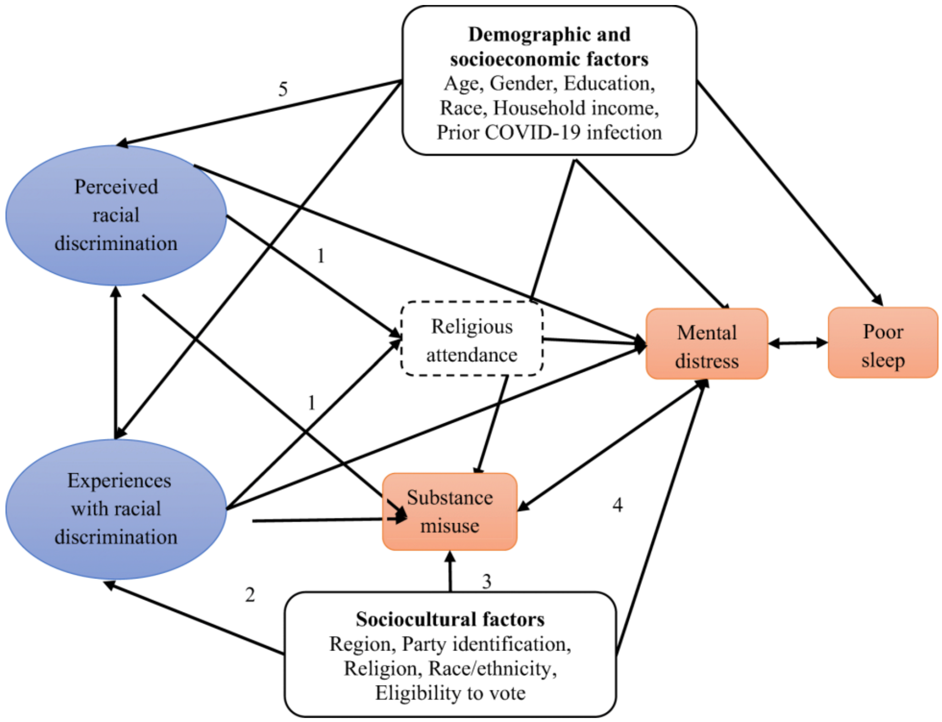
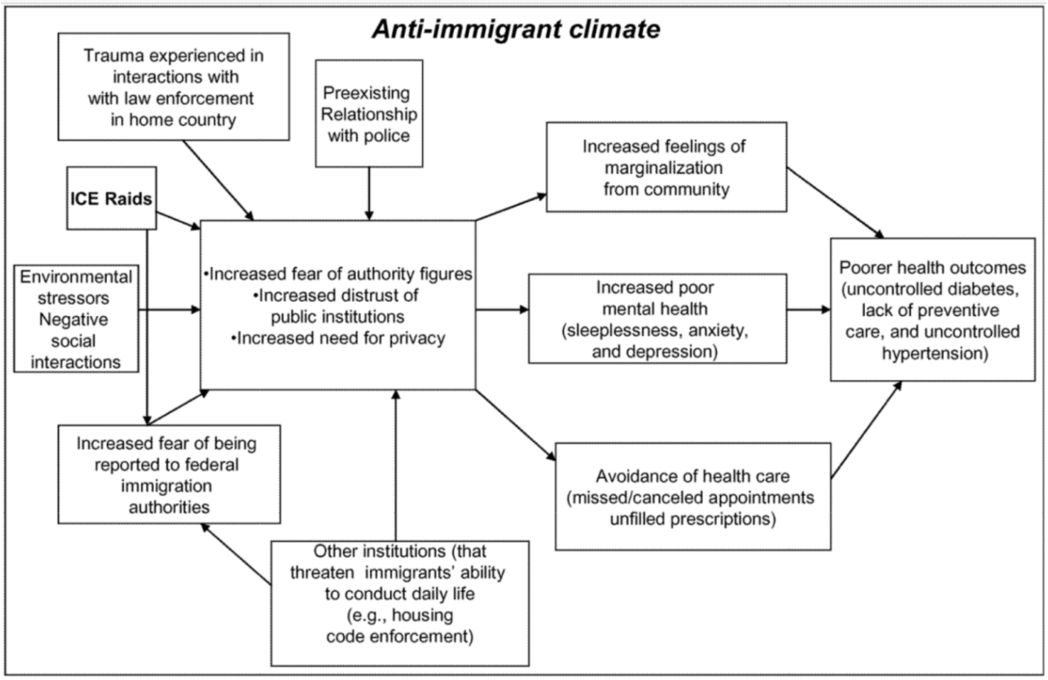


Figure 3. 2: Immigration Enforcement and Healthcare Avoidance among Undocumented Immigrants



Research Questions

The outcomes delineated below (mental health, COVID exposure and infection, healthcare use, sleep, and chronic pain) were chosen specifically because of data delineating the social and racialized production of these outcomes[104,118–124]. Self-reported health will not be used as an outcome since health perceptions are conditional on health access, particularly for latent diseases such as hypertension or mild-to-moderate diabetes. While the relationship between self-reported health and mortality has been demonstrated in meta-analyses[125], few studies test the long-term relationship within the United States among non-geriatric populations, and particularly within racial minorities in the United States, who might be excluded from health care interactions that might inform their health status (particularly for diseases predominately diagnosed by screening such as hypertension and diabetes), an exclusion exaggerated by immigrant status[126]. Similarly, other "silent" diseases that are screening dependent are not eligible to be included as outcomes.

Aim 1: Do undocumented Black immigrants have different health utilization, mental health profile, and sleep than Black immigrants and US-born Black individuals?

H1: Undocumented Black immigrants have profiles that are worse (less health utilization, worse mental health, and sleep) than Black immigrants and US Born non-Hispanic White persons but better than US-born Black persons.

Aim 2: Do undocumented Black immigrants have different health care utilization, COVID exposure, mental health profile, and sleep/chronic pain than other undocumented immigrants?

H2: Undocumented Black immigrants have less health utilization, more COVID exposure, worse mental health, chronic pain, and sleep than other undocumented immigrants and US Born non-Hispanic White persons.

Methodology

Data Source

The following analysis takes advantage of the 1999-2021 waves of National Health Interview Survey (NHIS), which is the nation's largest health survey administrated by the National Center for Health Statistics of the Centers for Disease Control and Prevention (CDC). In operation since 1957, the National Health Survey interviews an average of approximately 87,500 individuals annually on topics ranging from health behaviors, health conditions and health care utilization. All items are self-reported. Data were extracted from Integrated Public Use Microdata Series (IPUMS), which is administered by the University of Minnesota.

Outcome

Of particular interest are three categories of questions:

a) What are the differences in health care utilization and health insurance access?

b) What are the differences in perceived mental health?

c) What are the differences in sleep?

Table 3. 1: Measures

Outcome	Measure
Health Care Utilization	This will be operationalized via three variables: a binary variable indicating health insurance access, a binary variable indicating more than two years since last clinicians visit for individuals over 40 years, a binary variable representing whether the respondent had any hospitalizations in the previous 12 months for individuals over 40 years.
Mental Distress	Kessler Score greater than 13 will indicate severe mental distress
Sleep	Hours of Sleep (numeric scale)

Determinants	Measure
Race, Ethnicity, Immigration Status	Self-reported except for undocumented status, which is deduced by proxy measures as listed in *Methods: Identification*. See *Methods: Racial, Ethnic, and Immigrant Identity Construction* for details on how racial and ethnic identities are constructed
Racial Discrimination/Structural Racism	Measured by proxy of self-reported race/ethnicity and immigration status
Age, Gender	Self-reported Gender (Male/Female only)
Religious Attendance/Religious community membership	Not measured
Substance use	Not measured
Education	Not measured
Interactions with law/immigration enforcement	Not Measured
Health status	Health status is measured as part of a 5-item Likert Scale.
Health insurance	Self-reported health insurance access (NHIS-transformed binary variable indicating coverage by any insurance program

	(determined by asking if respondent had VA, Private health insurance, Medicaid, CHIP, or Medicare)

Identification

Identification will be carried out by the residual (logical imputation) method, developed by Borjas et al[127]. The residual method has been used to identify undocumented immigrants in national surveys by many immigration researchers, as well as the liberal and conservative think tanks and the Department of Homeland Security. The residual method identifies foreign born respondents and subtracts out the legally authorized immigrant population according to characteristics that theoretically would be accessible to legally authorized immigrants.

Ideally individuals who are foreign born are considered undocumented if they do not fit any of the following criteria:

1) They arrived in the US before 1980 (otherwise they would have been eligible for amnesty under the Immigration Reform and Control Act).
2) They are naturalized US citizens;
3) They receive Social Security Benefits, Medicaid, Medicare or Military insurance;
4) They have ever served in the Armed Forces;
5) They work in the government sector;
6) They or their spouse reside in public housing or receive housing subsidies;
7) They were born in Cuba;
8) Their occupation requires some licensing (e.g., physicians, registered nurses, air traffic controllers, and lawyers;
9) Their spouse is a legal immigrant or US citizen;

10) They meet the following characteristics which might indicate they are H1-B visa holders:

    a. They work in an occupation that commonly employs H-1B visa holders (such as computer programmer, physician, financial analysis, engineers, accountant, architect, chemist, lawyers);
    b. They have resided in the United States for six years or fewer (i.e., the maximum length of time an H-1B visa is valid);
    c. They are at least college graduates.

Other approaches have been taken to identify undocumented immigrant populations using approaches that assign probabilities of being undocumented using survey characteristics or machine learning, however, they have not been as widely adopted.[128–131]

While all these data are available for some surveys (such as the American Community Survey), the NHIS does not include data on all these characteristics in its public use dataset, and as such represents an approximation; nonetheless the NHIS has been used to study undocumented populations.

Racial, Ethnic, and Immigrant Identity Construction:

The NHIS provides the following racial categories, as harmonized by IPUMS: *White only*, *Black/African American only*; *American Indian/Alaska Native only*; *Asian only* ; and various permutations of *Other Race*, *Multiple Race*, and *Unknown*. Ethnicity variables are provided as *Not Hispanic/Spanish origin*; *Mexican; Mexican-American; Puerto Rican; Cuban/Cuban American*; *Dominican (Republic)*; and various permutations of *Other Hispanic*, *Multiple*

Hispanic, and *Unknown*. Survey items identify if a person is US born or not as well as whether they are citizens.

The first series of models will compare outcomes between undocumented Black immigrants, Black foreign-born, and Black US-born population in the following construction: 1) White Non-Hispanic, US born citizens (reference group), 2) Black US-born, 3) Black naturalized citizen, 4) Black documented immigrant, and 5) Black undocumented immigrant. The second series of models will compare outcomes between undocumented Black immigrants and other immigrant groups in the following fashion: 1) White Non-Hispanic, US born citizens (reference group) and undocumented immigrants who are 2) White Hispanic/non-Hispanic 3) Asian Hispanic/non-Hispanic, 4) Black Hispanic/non-Hispanic, 5) American Indian Hispanic/non-Hispanic, American Indian is included as 90% of American Indians categorized as undocumented were Hispanic.

Race and Ethnicity in this context serve as proxy variables for recipients of racism as differentially applied to non-White populations in the United States. While some studies have compared Black immigrants to other Black populations, this study will use White non-Hispanic US-born as a referent group. This is not to center “whiteness” as a health standard, but rather to decompose the separate paths that undocumented immigrants can take in response to legal exclusion. A sensitivity analysis will interact Hispanic ethnicity with race to account for the intersection of both constructs.

Model and Covariates

I employ logistic regression models, with fixed effects for survey year and the use of complex survey weights. Model 1 will be used for all non-sleep outcomes:

$$\log(Y_{it}) = \beta_0 + \beta_1 Race/status_{it} + \beta_2 age_{it} + \beta_3 education_{it} + \beta_4 gender_i + $$
$$+\beta_5 censusregion_{it} + e_{it}$$

Race/status will be replaced with immigration status for models identifying effects across Black immigration status and separately by race/ethnicity interactions for undocumented immigrants. Covariates will include age (as deciles), education, reported gender, and US census region. Hours of sleep will be represented as a linear regression since hours of sleep in this study is normally distributed:

$$Y_{it} = \beta_0 + \beta_1 Race/status_{it} + \beta_2 age_{it} + \beta_3 education_{it} + \beta_4 gender_i + \; +$$
$$\beta_6 censusregion_{it} + e_{it}$$

Results

The data from 1999-2018, when weighted, represent 298.9 million individuals (weighted from 1.9 million observations), of whom 13% (38.9 million) are foreign born. Of those who are foreign born, 47.5% (18.5 million) were citizens, 33.2% (12.9 million) were undocumented, and 19.2% (7.5 million) are documented immigrants. This broadly matches numbers given as part of general national statistics[132,133].

Table 3. 2: Undocumented Immigrants, by Race

	Non-Hispanic White	Hispanic White	Non-Hispanic Black	Hispanic Black	Non-Hispanic Native American	Hispanic Native American	Non-Hispanic Other/Multiple Race	Hispanic Other/Multiple Race	Non-Hispanic Asian	Hispanic Asian
% of Sample	11.9	57.1	6.2	1.1	0.1	1.2	0.4	3.5	17.9	0.6
Age (Standard Deviation)	36.8 (12.2)	34.1 (10.3)	34.6 (11.0)	35.6 (10.3)	33.3 (9.2)	35.6 (8.9)	35.9 (11.3)	31.8 (11.4)	33. (10.7)	36.5 (9.9)
Female (%)	49.7	43.6	45.3	44.0	48.0	42.0	50.6	43.5	50.4	41.5%
Region of US (%)										
Northeast	29.1	10.1	36.1	26.3	30.2	6.4	18.0	16.6	22.2	11.4
North Central	19.6	9.6	13.8	9.0	13.6	9.7	15.9	11.9	16.9	6.2
South	27.3	39.3	43.3	42.7	36.7	25.3	19.5	35.7	26.7	21.9
West	24.1	41.0	6.8	22.0	19.4	58.6	46.6	35.9	34.2	60.6
Time spent in the US (%)										
Less than 1 year	5.7	2.2	3.6	1.9	6.7	1.7	0.8	3.1	5.0	1.0
1-5 years	30.9	17.7	29.7	17.6	19.9	12.6	42.7	26.3	33.9	15.1
5-10 years	23.7	22.5	26.7	25.3	47.3	23.2	17.0	22.9	29.0	15.3
10-15 years	13.7	21.9	17.0	21.8	8.4	22.1	13.1	20.8	15.6	21.0
15 years or more	26.0	35.8	23.0	33.5	17.8	40.4	26.4	26.8	16.6	47.6
Educational Attainment (%)										
Grade 12 or less	22.8	65.2	26.1	58.5	9.4	74.7	29.7	69.2	20.1	57.3
High school diploma or GED	20.3	20.3	26.7	23.8	13.6	15.6	31.5	16.7	13.0	23.6
Some college	20.9	9.5	26.7	10.6	11.0	8.0	22.3	8.9	15.6	11.0
Bachelor's Degree	20.7	3.9	13.5	4.9	29.6	1.3	12.3	3.4	25.9	5.9
Master's/Professional/Doctoral Degree	15.2	1.2	6.9	2.2	36.5	0.4	4.2	1.8	25.5	2.2

Table 3. 3: Black populations, by legal status

	US Born Citizens	Naturalized Citizens	Documented Immigrant	Undocumented Population
% of Sample	90.3%	5.2%	2.0%	2.5%
Age (Mean, Standard Deviation)	32.6 (16.5)	43.9 (11.7)	35.6 (11.1)	34.7 (11.4)
Female (%)	53.8	53.1	53.1	45.1
Hispanic (%)	3.142	10.3	14.7	14.7
Region of US (%)				
South	58.8	40.2	35.1	43.2
Northeast	14.5	41.5	40.4	34.7
North Central/Midwest	18.5	9.5	12.5	13.1
West	8.1	8.7	12.0	9.0
Time spent in US (%)				
Less than 1 year	--	0.1	2.8	3.3
1 year to less than 5 years	--	2.7	27.9	27.9
5 years to less than 10 years	--	8.8	25.6	26.5
10 years to less than 15 years	--	15.4	14.4	17.7
15 years or more	--	73.0	29.3	24.6
Educational Attainment (%)				
Never attended school/kindergarten only	3.9	0.9	2.9	2.6
Grade 12 or less	34.9	14.9	29.5	28.3
High school diploma or GED	23.6	22.7	24.5	26.3
Some college	24.7	31.4	23.1	24.3
Bachelor's Degree	8.7	19.7	13.8	12.3
Master's/Professional/Doctoral Degree	4.1	10.5	6.3	6.2

Health Insurance and Healthcare Utilization:

See eTable 3.1-3.2 for individual coefficients. Except for non-Hispanic Native Americans, all groups of undocumented immigrants had higher odds of being uninsured than White non-Hispanic citizens. Upon further inspection, Hispanic subgroups tended to have higher odds than other immigrants (Figure 3.3). Black undocumented immigrants had higher odds of uninsurance than other White non-Hispanic citizens (OR 6.4 95% CI 5.6, 7.2) (Figure 3.4). Similar trends were found for recent clinician visits for individuals over the age of 40; most categories of undocumented immigrants had significantly higher odds ratios of no provider visits in the prior 2 years, with higher point estimates for Hispanic Blacks (OR 4.2, 95% CI 2.6, 6.8) and Hispanic Asians (OR 4.5, 95% CI 2.1, 9.5). (Figure 3.5). Among Black respondents, the odds ratio of having no recent encounters trended upwards with less secure legal status, with lower odds for Black US Born Citizens (OR 0.9, 95% CI 0.9, 1.0) and higher odds ratios for Black undocumented immigrants (OR 2.5, 95% 2.1, 3.1) (Figure 3.6).

Over the age of 40, most categories of undocumented immigrants had significantly lower overnight hospitalization odds than NHWC, with lowest odds for Hispanic Asians (OR 0.2 95% CI 0.1, 0.9), Hispanic Blacks (OR 0.2 95% CI 0.1, 0.6) and Hispanic Native Americans (OR 0.3 95% CI 0.1, 0.8) (Figure 3.7). Compared to NHWC, Black US Born Citizens had higher (OR 1.2, 95% CI 1.1, 1.2) and Black undocumented immigrants had lower (OR 0.5, 95% CI 0.4, 0.7) odds of hospitalization in the previous year. (Figure 3.8).

Figure 3. 3: Probability of being uninsured, among undocumented immigrants

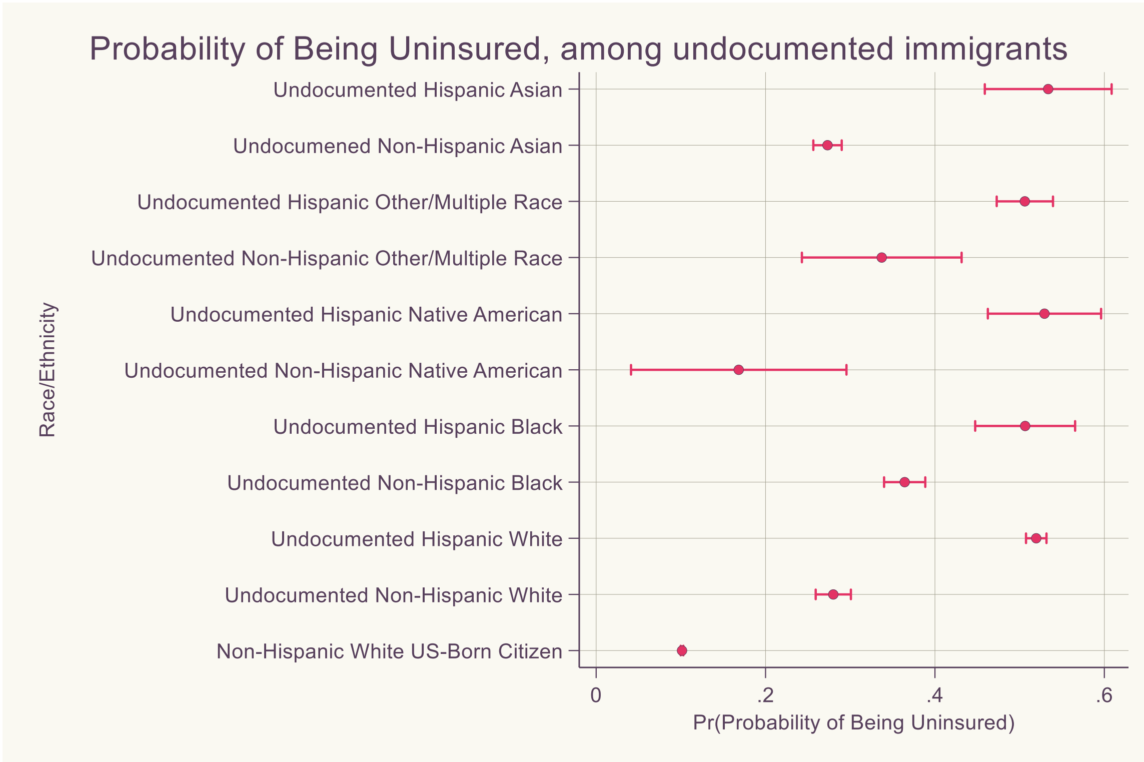


Figure 3. 4: Probability of being uninsured, among Black immigrants, across legal strata

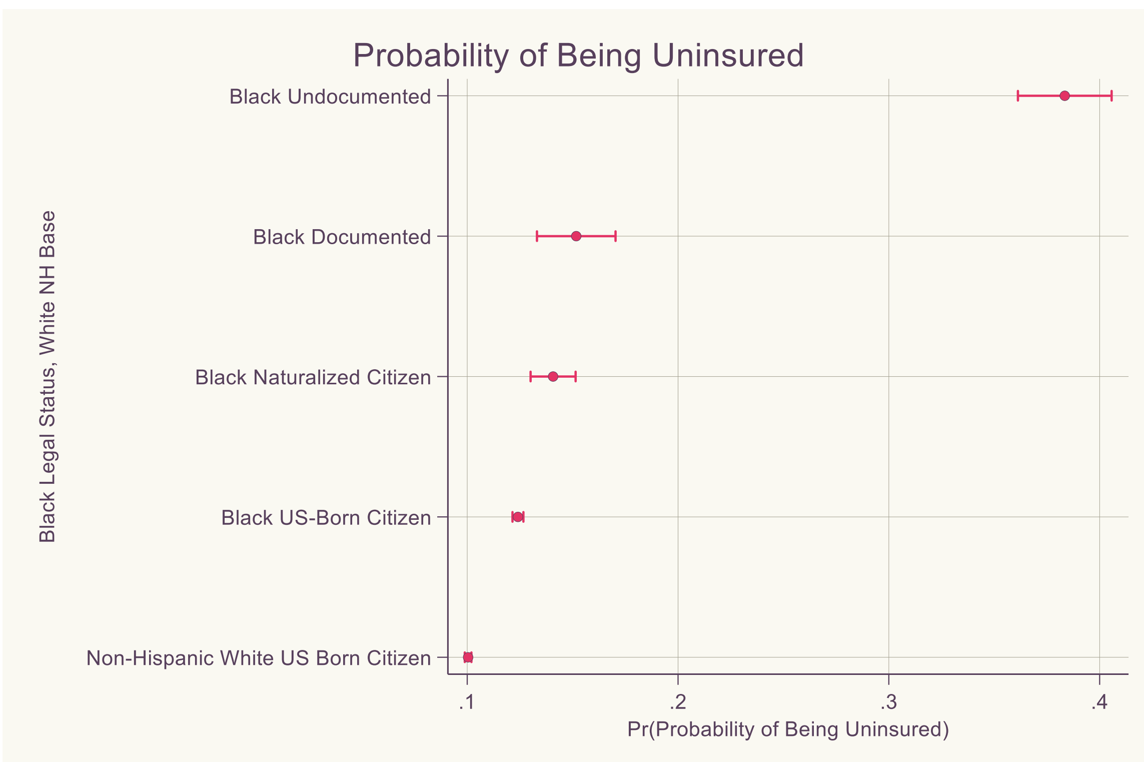


Figure 3. 5: Probability of No Doctor Visit in the Previous 2 years, across race ethnicity

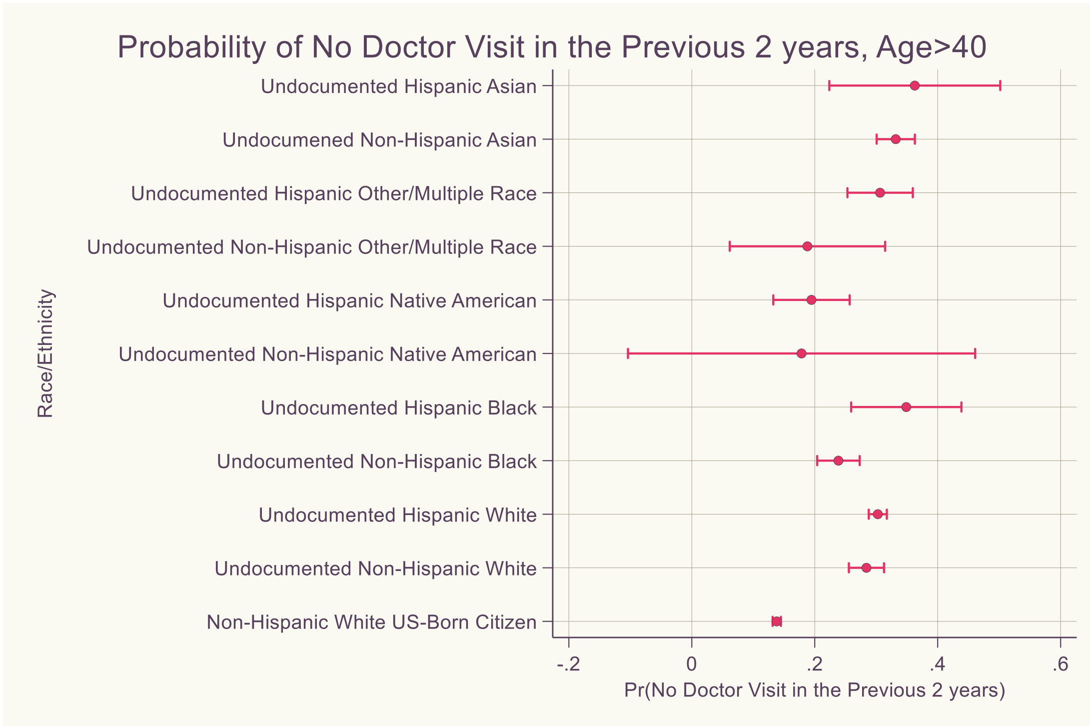


Figure 3. 6: Probability of No Doctor Visit in the Previous 2 years, across legal strata

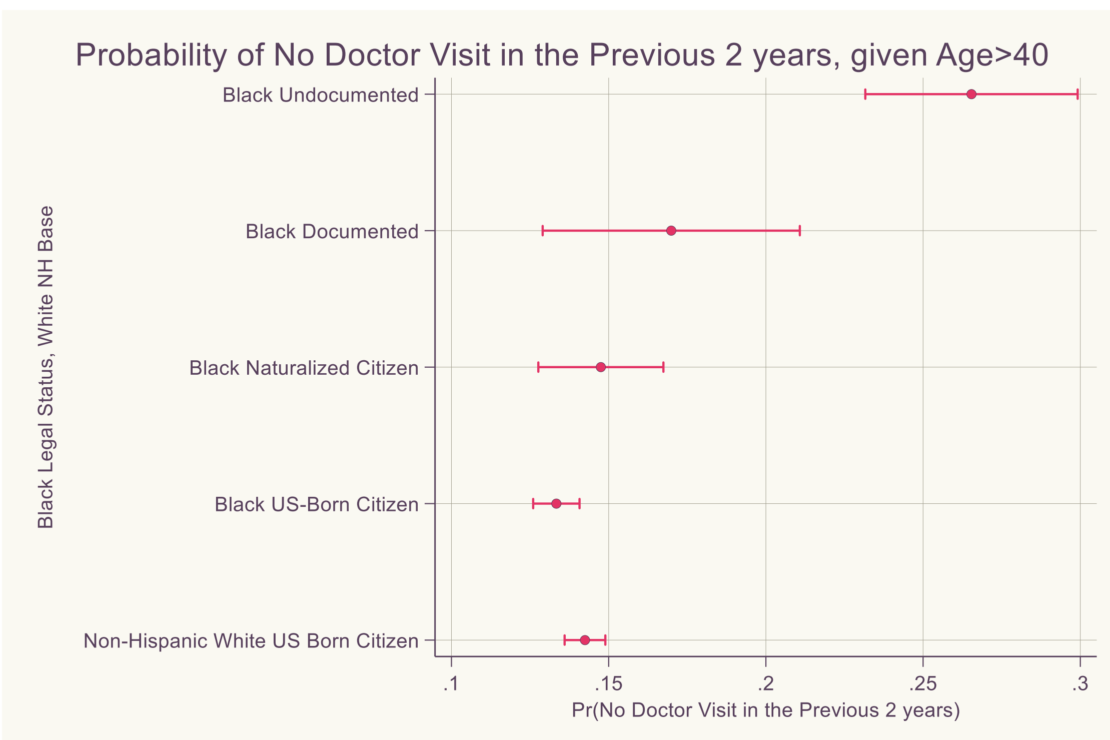


Figure 3. 7: Probability of Overnight Stay in Previous 12 months, across race/ethnicity

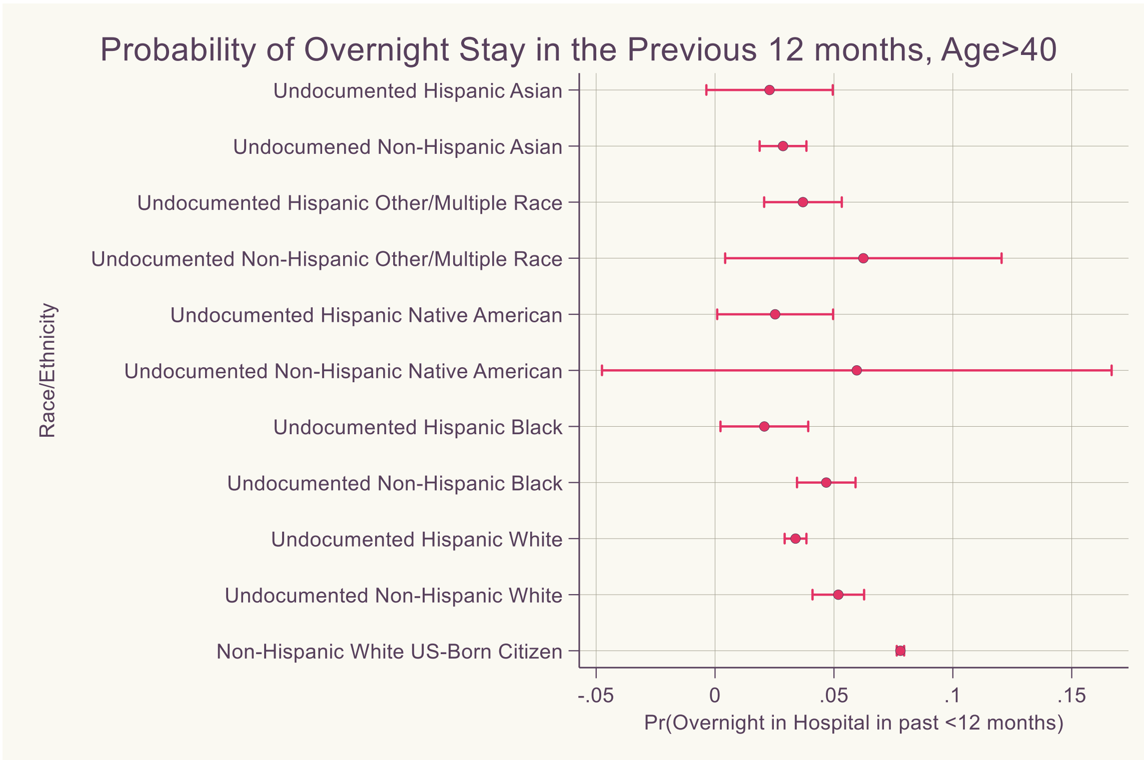
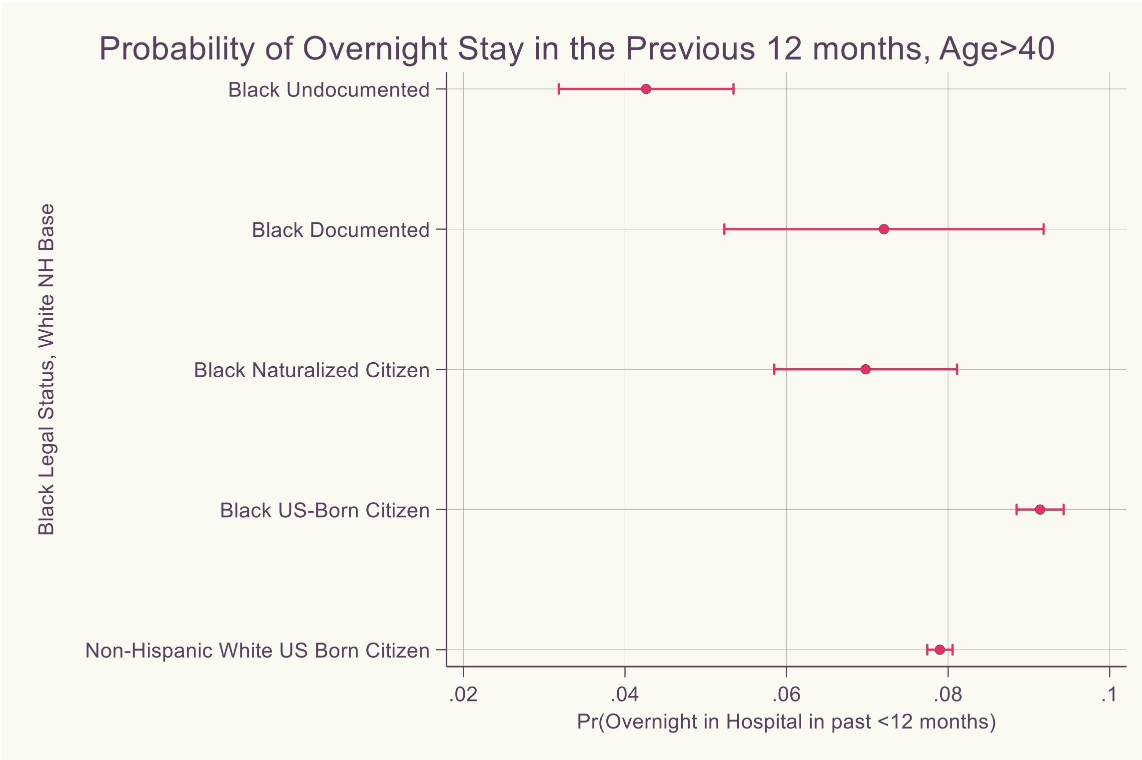


Figure 3. 8: Probability of Overnight Stay in Previous 12 months, across legal status



Mental Distress and Sleep

Among undocumented immigrants, severe mental distress and sleep was similar across race and ethnicities, although largely lower than NHWC (Figure 3.9). ORs of mental distress for all Black respondents were lower than NHWC; within that strata point estimates were higher for Black US Born Citizens (OR 0.9, 95% CI 0.8, 0.9) (Figure 3.10). Undocumented non-Hispanic Black respondents had significantly lower amounts of sleep than NHWC (-0.1 hours, 95% CI -0.2, -0.03) and lower point estimates other undocumented respondents (Figure 3.11). Compared to NHWC, Black US Born (-0.1 hours, 95% CI -0.1, -0.1) and Naturalized Citizens (-0.2 hours, 95% CI -0.2, -0.2) (Figure 3.12).

Figure 3. 9: Probability of Severe Mental Distress, across race/ethnicity

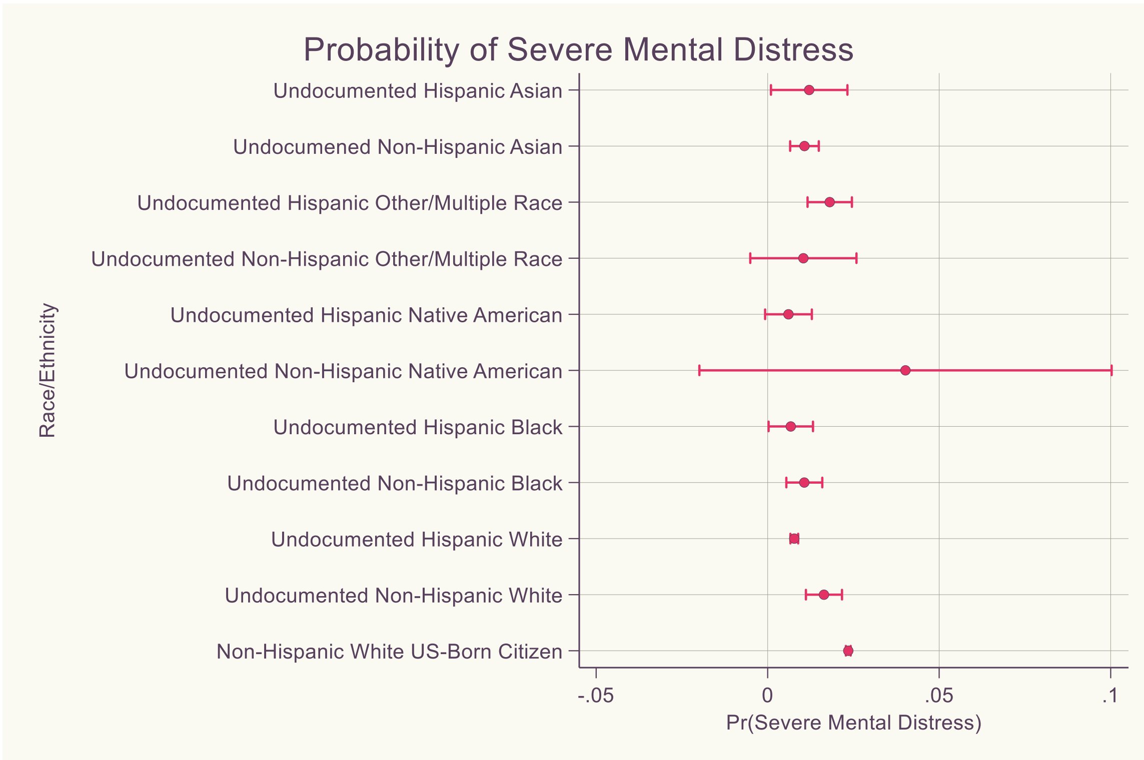


Figure 3. 10: Probability of Severe Mental Distress, across legal status

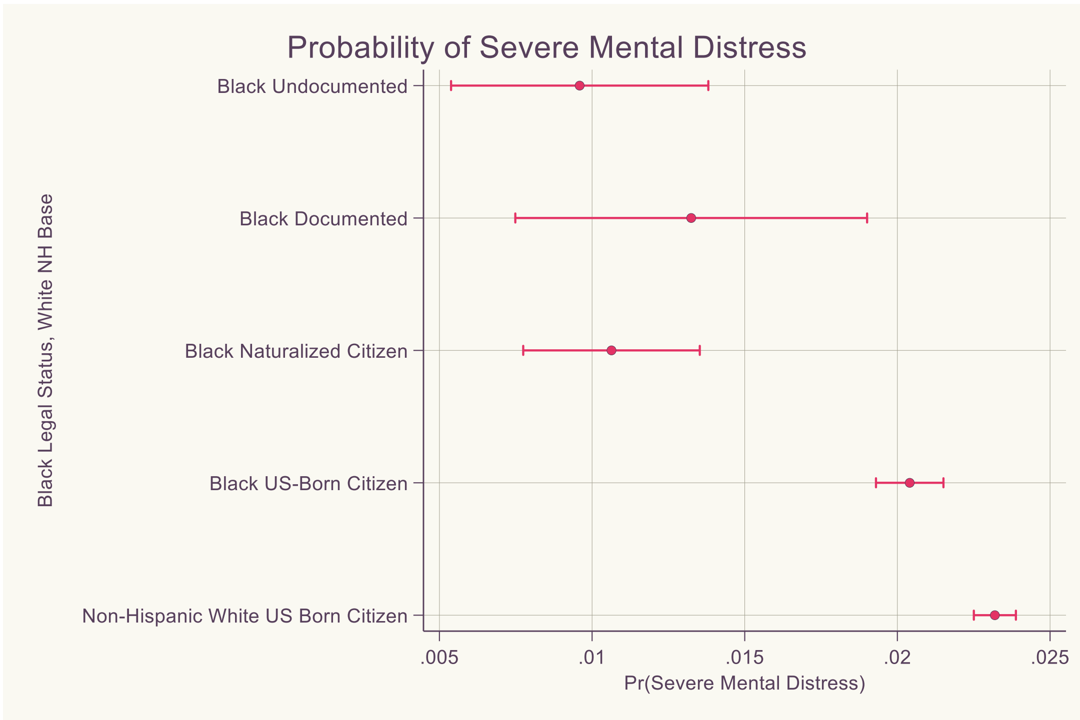


Figure 3. 11: Hours of Sleep, across Race/Ethnicity

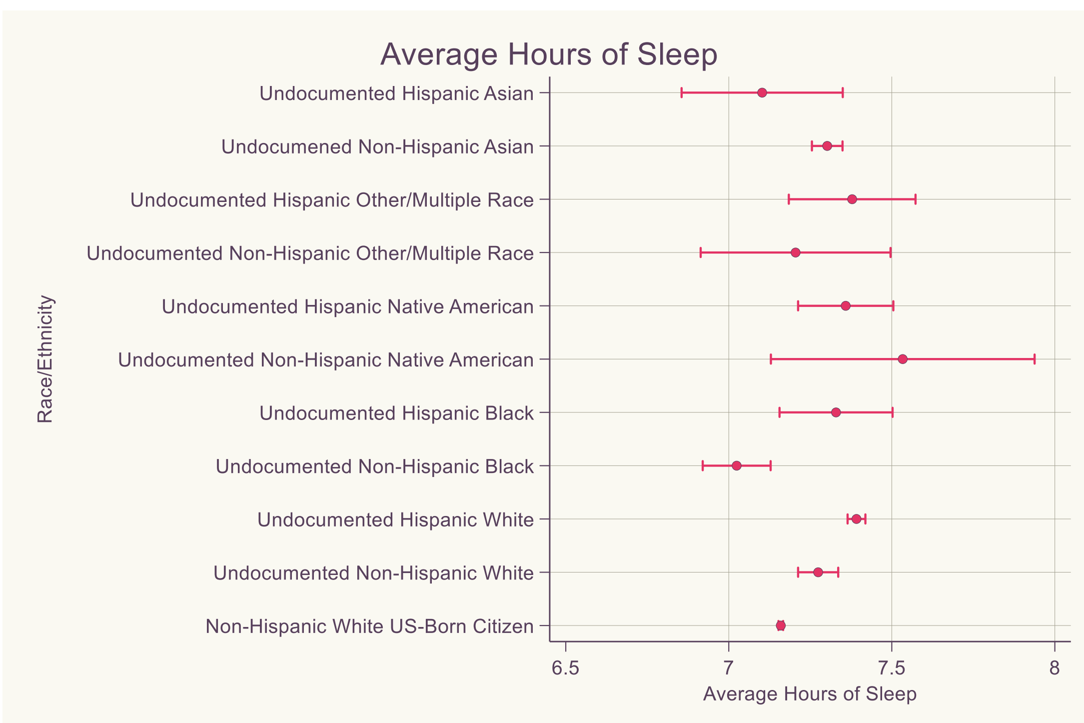
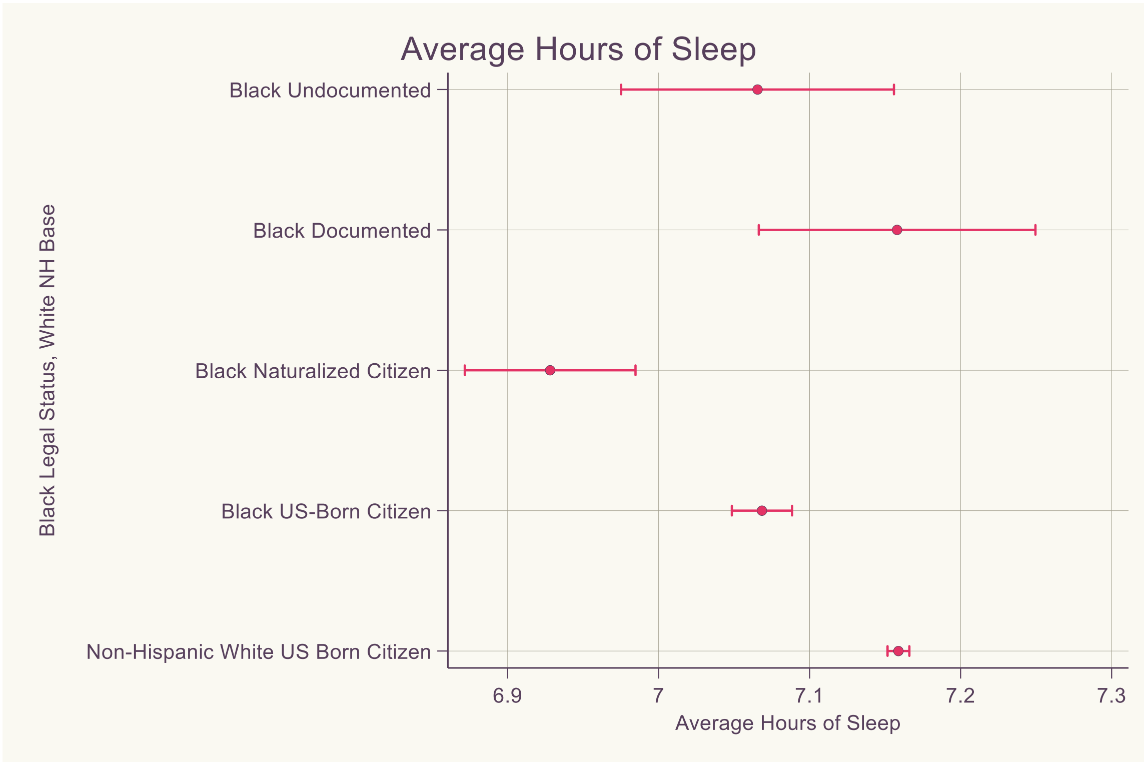


Figure 3. 12 Hours of Sleep, across legal status



Discussion

This study demonstrates differences in healthcare and insurance access along strata of legal status, race and ethnicity. Among Black individuals, undocumented immigrants had statistically lower rates of insurance and hospitalizations and non-statistically significant higher rates of no clinician visits in the previous 2 years. Among undocumented immigrants, virtually all groups had lower rates of insurance access (with higher rates of uninsurance for Hispanic immigrants), with higher rates of no provider encounters for Hispanic Blacks and Hispanic/non-Hispanic Asians, and lower rates of hospitalizations across non-Hispanic White and Hispanic categories. Finally, there was no statistically significant relationship between mental distress and sleep.

Rather than a single uniform effect of stratification within US society, these findings illustrate the complex intersected ways in which racism and legal exclusion act on immigrants and Black individuals. Legal exclusion, particularly from health insurance, leads to lower uptake of primary care and overall longer amounts of time away from clinician care. This legal status effect was seen particularly among Black individuals. Among undocumented status overall, individuals across racial and ethnic categories had less odds than NWHC to have insurance or to have seen a physician. This did not correlate to increased hospitalization risk, however, demonstrating the potential persistence of the immigrant paradox.

There was no clear differential impact of legal status or race/ethnicity on severe mental distress, although non-Hispanic Black immigrants might have shorter sleep durations (with even lower sleep durations among Black citizens), which might be due either to stress or other environmental factors. Prior research demonstrates that past trauma and current stress contribute to poor sleep quantity or quality, while shorter tenure in the United States might be associated with greater sleep among immigrants [134–137]. Earlier work schedules might also contribute to worse sleep, a part of well described "time scarcity" affecting marginalized persons.[138] More research should be done in identifying signs of potential latent stress in this group aside from Kessler scores.

It is concerning that Hispanic undocumented immigrants had higher odds of uninsurance awithin the previous 2 years, across racial categories. A Blinder-Oaxaca decomposition of NHIS reported access to care disparities among Hispanic immigrants might be driven by region of residence and health insurance differences, more likely than language and citizenship status[139]. However, Medicaid expansion contributed little to improving disparities among this group[140]. This of course, does not even address health coverage for adult undocumented immigrants, which only exists statewide in California, Colorado, Illinois, New York, Oregon, Washington and DC via Marketplace, Medicaid, and state funds[141]. This points towards the need for targeted policy solutions and outreach to improve health insurance coverage among undocumented immigrants as a whole.

Limitations include that this data is from repeated cross-sectional survey data from 1999 and 2018 from a representative sample and reflects an approximation to nationwide trends from that period. Further work is necessary to consider the impact racial and legal exclusion in determining healthcare outcomes.

Conclusion

There is a complicated relationship between legal status, ethnicity, and race in health insurance access and healthcare utilization, with marginalization affecting groups across all three axes.

Supplement

eTable 3. 1: Regression Coefficients for Black Individuals

	Uninsured	No Clinician Visit in >2 years	Overnight Hospitalization	Severe Mental Distress	Hours of Sleep
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	Beta (95% CI)
main					
Non-Hispanic White US Born Citizen	Base	Base	Base	Base	Base
Black US-Born Citizen	1.295***	0.919**	1.165***	0.875***	-0.090***
	[1.256,1.336]	[0.867,0.975]	[1.123,1.209]	[0.822,0.932]	[-0.111,-0.068]
Black Naturalized Citizen	1.520***	1.051	0.865	0.448***	-0.225***
	[1.377,1.678]	[0.881,1.255]	[0.723,1.036]	[0.339,0.592]	[-0.282,-0.168]
Black Documented	1.676***	1.280	0.895	0.561*	0.005
	[1.427,1.969]	[0.913,1.794]	[0.659,1.217]	[0.359,0.876]	[-0.088,0.097]
Black Undocumented	7.142***	2.522***	0.506***	0.404***	-0.089
	[6.363,8.016]	[2.051,3.101]	[0.386,0.665]	[0.258,0.632]	[-0.180,0.001]
Northeast	Base	Base	Base	Base	Base
North Central/Midwest	1.307***	1.241***	1.058**	1.096*	0.072***
	[1.239,1.377]	[1.164,1.324]	[1.014,1.105]	[1.007,1.192]	[0.052,0.092]
South	1.930***	1.233***	1.068**	1.270***	0.097***
	[1.837,2.029]	[1.156,1.314]	[1.024,1.114]	[1.175,1.372]	[0.078,0.117]
West	1.642***	1.491***	0.918***	1.225***	0.135***
	[1.551,1.739]	[1.381,1.609]	[0.876,0.963]	[1.124,1.336]	[0.114,0.156]
Sex	0.830***	0.467***	1.014	1.531***	0.029***
	[0.811,0.850]	[0.448,0.487]	[0.986,1.043]	[1.457,1.609]	[0.017,0.041]
Grade 12 or less, no high school diploma or equivalent	Base	Base	Base	Base	Base
High school diploma or GED	0.753***	0.796***	0.741***	0.480***	-0.065***
	[0.722,0.787]	[0.749,0.845]	[0.710,0.773]	[0.448,0.514]	[-0.092,-0.038]
Some college, no 4yr degree	0.469***	0.576***	0.745***	0.339***	-0.151***
	[0.449,0.490]	[0.539,0.616]	[0.714,0.776]	[0.316,0.364]	[-0.177,-0.124]
Bachelor's degree (BA,AB,BS,BBA)	0.199***	0.434***	0.554***	0.126***	-0.074***
	[0.188,0.210]	[0.403,0.468]	[0.526,0.584]	[0.114,0.139]	[-0.101,-0.047]
Master's, Professional, or Doctoral Degree	0.131***	0.314***	0.522***	0.095***	-0.079***
	[0.121,0.142]	[0.285,0.346]	[0.493,0.554]	[0.082,0.109]	[-0.107,-0.051]
0-9	Base			Base	
10-19	1.515***			0.133***	Base
	[1.422,1.614]			[0.106,0.166]	
20-39	7.576***			2.336***	-0.533***
	[7.090,8.094]			[2.073,2.633]	[-0.583,-0.484]
40-59	4.295***	Base	Base	3.153***	-0.655***
	[4.016,4.593]			[2.799,3.551]	[-0.703,-0.606]
60-79	1.003	0.444***	1.838***	1.594***	-0.292***

	[0.930,1.081]	[0.423,0.465]	[1.781,1.897]	[1.415,1.797]	[-0.342,-0.242]
80-	0.045***	0.216***	3.028***	1.000	0.229***
	[0.032,0.063]	[0.194,0.240]	[2.896,3.167]	[1.000,1.000]	[0.173,0.285]

eTable 3. 2: Regression Coefficients for Undocumented Immigrants

	Uninsured	No Clinician Visit in >2 years	Overnight Hospitalization	Severe Mental Distress	Hours of Sleep
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	Beta (95% CI)
main					
Non-Hispanic White US-Born Citizen	Base	Base	Base	Base	Base
Undocumented Non-Hispanic White	4.018***	2.900***	0.636***	0.689*	0.115***
	[3.559,4.537]	[2.438,3.449]	[0.507,0.799]	[0.495,0.958]	[0.053,0.177]
Undocumented Hispanic White	13.885***	3.231***	0.390***	0.321***	0.232***
	[13.051,14.773]	[2.956,3.533]	[0.337,0.451]	[0.275,0.374]	[0.203,0.261]
Undocumented Non-Hispanic Black	6.371***	2.181***	0.568***	0.444**	-0.135*
	[5.606,7.240]	[1.746,2.724]	[0.427,0.755]	[0.269,0.733]	[-0.239,-0.031]
Undocumented Hispanic Black	13.009***	4.187***	0.236**	0.278*	0.169
	[9.693,17.457]	[2.574,6.811]	[0.094,0.593]	[0.105,0.737]	[-0.004,0.343]
Undocumented Non-Hispanic Native American	1.901	1.421	0.759	1.763	0.374
	[0.687,5.262]	[0.153,13.222]	[0.108,5.336]	[0.353,8.809]	[-0.031,0.779]
Undocumented Hispanic Native American	14.576***	1.604*	0.285*	0.250*	0.199**
	[10.414,20.402]	[1.009,2.551]	[0.104,0.778]	[0.080,0.778]	[0.053,0.345]
Undocumented Non-Hispanic Other/Multiple Race	5.524***	1.528	0.790	0.432	0.045
	[3.338,9.140]	[0.582,4.009]	[0.283,2.203]	[0.095,1.968]	[-0.246,0.337]
Undocumented Hispanic Other/Multiple Race	12.984***	3.303***	0.424***	0.762	0.219*
	[11.005,15.321]	[2.434,4.481]	[0.265,0.679]	[0.525,1.105]	[0.024,0.414]
Undocumented Non-Hispanic Asian	3.861***	3.813***	0.340***	0.446***	0.142***
	[3.496,4.264]	[3.209,4.529]	[0.237,0.487]	[0.299,0.665]	[0.095,0.189]
Undocumented Hispanic Asian	14.901***	4.512***	0.262*	0.504	-0.057
	[10.236,21.691]	[2.142,9.507]	[0.078,0.872]	[0.196,1.296]	[-0.305,0.190]
Northeast	Base	Base	Base	Base	Base
North Central/Midwest	1.184***	1.222***	1.070**	1.079	0.068***
	[1.120,1.252]	[1.144,1.305]	[1.023,1.120]	[0.986,1.181]	[0.048,0.089]
South	1.791***	1.192***	1.108***	1.317***	0.081***
	[1.700,1.886]	[1.117,1.273]	[1.060,1.158]	[1.211,1.432]	[0.062,0.101]
West	1.512***	1.406***	0.933**	1.219***	0.131***
	[1.429,1.600]	[1.303,1.517]	[0.888,0.981]	[1.114,1.333]	[0.110,0.152]
Sex	0.863***	0.464***	1.008	1.553***	0.034***
	[0.841,0.885]	[0.445,0.485]	[0.978,1.039]	[1.472,1.639]	[0.022,0.047]
Grade 12 or less, no high school diploma or equivalent	Base	Base	Base	Base	Base
High school diploma or	0.742***	0.791***	0.737***	0.486***	-0.041**

GED					
	[0.709,0.777]	[0.743,0.843]	[0.703,0.773]	[0.450,0.525]	[-0.068,-0.014]
Some college, no 4yr degree	0.457***	0.584***	0.731***	0.338***	-0.100***
	[0.436,0.479]	[0.545,0.625]	[0.697,0.766]	[0.312,0.365]	[-0.126,-0.074]
Bachelor's degree (BA,AB,BS,BBA)	0.196***	0.446***	0.549***	0.130***	-0.012
	[0.185,0.207]	[0.414,0.480]	[0.518,0.581]	[0.117,0.144]	[-0.040,0.016]
Master's, Professional, or Doctoral Degree	0.115***	0.316***	0.521***	0.099***	-0.018
	[0.105,0.125]	[0.286,0.349]	[0.489,0.555]	[0.086,0.116]	[-0.046,0.011]
0-9	Base			Base	
10-19	1.477***			0.125***	Base
	[1.386,1.574]			[0.097,0.162]	
20-39	6.359***			2.260***	-0.529***
	[5.943,6.805]			[1.996,2.558]	[-0.583,-0.475]
40-59	3.682***	1.000	1.000	3.061***	-0.654***
	[3.442,3.939]	[1.000,1.000]	[1.000,1.000]	[2.704,3.466]	[-0.707,-0.601]
60-79	0.910*	0.448***	1.915***	1.568***	-0.292***
	[0.844,0.982]	[0.426,0.471]	[1.850,1.982]	[1.381,1.781]	[-0.346,-0.238]
80-	0.068***	0.213***	3.213***	1.000	0.229***
	[0.050,0.091]	[0.190,0.238]	[3.063,3.370]	[1.000,1.000]	[0.167,0.291]

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