Relationship between Immigration of Medical Professionals and Health Measures

Alice Peng

Seniors Honors Thesis
Economics
University of North Carolina at Chapel Hill

April 28, 2021

1 Introduction

In the United States, the shortage of primary care medical professionals is an ever-evolving and worsening problem. With the current rate of population growth and the large aging population, researchers project that the United States will need more than "52,000 additional primary care physicians by 2025", with population growth driving much of this demand (Petterson et al., 2012). The difficulty in reaching this projected goal of tens of thousands of additional physicians is heightened by the lag in training medical labor, with most professionals earning a college degree before specializing in healthcare. Thus, any immediate policies would not have any effect until several years later. In the meantime, hundreds of thousands of people receive insufficient care. Moreover, the training lag is not the only complication in the shortage of medical professionals. On the contrary, the number of primary care health professionals is also decreasing, and the reasons for this decrease are difficult to quantify, ranging from the decreased prestige associated with the work, the inflexible schedule, and high cost of entry into the field (Lakhan & Laird, 2009). The consequence of this scarcity are patients who are unable to book routine doctor's appointments in an easy and timely manner. This difficulty then results in doctor's appointments encompassing multiple medical issues rather than just one, increasing the difficulty of the physician's work, especially when considering the tightened time constraints. Subsequently, the increasing difficulty of primary care work exacerbates the medical labor shortage as fewer and fewer individuals desire to enter this field. Ultimately, the multi-faced nature of the issues concerning the scarce supply of medical professionals illustrates the difficulty in quickly and easily addressing this problem.

The difficulty of alleviating the medical labor shortage motivates this paper to examine the relationship between foreign-born medical professionals and medical quality, viewing foreign-born medical professionals as a possible short-term solution to maintain care for citizens. Hence, in this paper, I study whether increased foreign medical results in benefits in medical quality by analyzing how the population of foreign-born medical professionals affects various health indicators. I implement a fixed effects model that uses the NHIS (National Health Interview Survey) and Current Population Survey (CPS) to analyze the relationship between the number of foreign-born medical professionals and quality of health measures. To answer the research question, lags on a longer dataset with more general geographic information as well as instrumental variables on a truncated dataset with more specific geographic information were utilized to address endogeneity problems.

This solution of foreign medical labor is especially pertinent when considering that the most-often implemented responses to this scarcity of medical labor has been to either cut funding to hospitals or assign more patients to the same physician. Obviously, both of these solutions can not be utilized long-term. Cutting funding and assigning more patients to the same physician would mean that each patient receives less time with the medical professional, resulting in missed symptoms and possible erroneous diagnoses. These issues are especially pertinent in rural areas where the mismatch between the supply and demand for primary care medical professionals is higher than other areas (Bodenheimer & Pham, 2010). Concretely, these stop-gap responses have resulted in more than "sixty-five million Americans liv[ing] in primary care shortage areas", with the majority of these Americans residing in rural areas (Bodenheimer & Pham, 2010). By introducing immigrant labor, the lag between training and care benefits is reduced, and the buoyed numbers of medical professionals increases the probability that underserved communities, especially rural ones, receive the care that they need.

This research paper will also strive to complement the studies done on the effects of leaving medical professionals on their home countries, often denoted as brain drain. Understanding both the benefits towards the receiving nation and home nation is essential to creating policy that does not have unforeseen consequences in the international community. Without clear benefits towards United States patients, the harm towards host countries becomes an important point to contemplate while drafting immigration policies for high-skilled labor.

The rest of the paper will proceed in the following manner: Section 2 is an overview of the related literature, and Section 3 is a review of the data with general trends outlined. Section 4 discusses the empirical model and the various means to reduce endogeneity, and Section 5 reports the results of various robustness checks. Finally, in conducting this analysis, I have generally found insignificant relationships between foreign-born medical professionals and quality of health. However, the strength of the relationship changes with the quality health measure and with the time period studied.

2 Related Literature

Many papers have studied the relationship between immigration of medical professionals and measures of health. However, these papers generally examine the effects on the exporting country, determining the extent or existence of the brain drain. In Poland, researchers, using surveys sent to medical professionals and Polish citizens, analyzed the movement of their medical workforce to other European Union countries, finding that the increased flight of their medical professionals has resulted in worse quality of health outcomes for their citizens (Żuk, Żuk, & Lisiewicz-Jakubaszko, 2019). However, other papers have found that the emigration of skilled laborers has more nuanced effects than a simple reduction of care quality on the exporting country; they found that emigration does not always result in brain drain of the exporting country. Instead, the researchers concluded that the innovation of the exporting country is what determines whether the exit of skilled professionals benefits or harms their intellectual trust (Agrawal, Kapur, McHale, & Oettl, 2011). Although the literature does not agree on the mechanism in which the emigration of foreign professionals can harm the exporting country, most researchers agree that if immigration policies are not well-considered, the leaving of medical professionals results in poorer health outcomes of the exporting country.

The harm results from the exporting country losing the monetary investments needed to train these workers as well as the workers themselves while the receiving country is unable to take advantage of the human capital of the immigrant medical professionals. In review papers, researchers consistently found that the emigration of health professionals exacerbated health inequities between high-income and low-income countries with low-income countries receiving increasingly worse care because of inadequate human and financial capital (Aluttis, Bishaw, & Frank, 2014). In one study, researchers showed that the emigration of 600 medical graduates from South Africa cost the nation $37 million and that out of more than 5000 registered medical professionals, only 600 work in public hospitals in the nation (Pang, Lansang, & Haines, 2002). When considering that many medical professionals in their receiving country often do not work in healthcare settings, with many taking unskilled jobs, their human capital is wasted with the exporting country taking most of the burden.

Without health professionals in the exporting country, there are fewer individuals able to implement health interventions in areas such as maternal health, HIV/AIDS outcomes, and malaria survival rates. Thus, their absence makes much of the aid given by other nations irrelevant as there is no one able to utilize their aid effectively (Kollar & Buyx, 2013). Furthermore, the leaving of highly skilled medical professionals means that the nation does not earn enough to fund the high cost education programs to develop this human capital, creating a vicious cycle of worsening health conditions. Thus, it is doubly important to investigate the relationship between immigrant medical professionals and health measures in the receiving country. This information is essential to making informed decisions regarding the possible benefits of policies that encourage the immigration of foreign medical professionals against the risks of the same policies harming the exporting country.

Moreover, these papers imply that although foreign immigration may be a short-term solution, it cannot be a long-term one. This conclusion is extended by Forcier, Simoens, & Giuffrida, 2004; from a study of the participating OECD (Organisation for Economic Co-operation and Development) countries, they surmised that a broad based policy must be implemented between multiple nations to ensure that no harm is being done to the exporting country's population when skilled medical workers leave (Forcier, Simoens, & Giuffrida, 2004). Without a connected approach between countries, lax immigration policies with higher income nations mean increased emigration of health workers from exporting countries, a phenomenon closely studied by Docquier & Rapoport, 2009. In their research, they saw that restrictions on immigration, especially from countries in West Africa with weak medical infrastructure, would immensely help the local economies and health systems. Hence, if not implemented carefully, the immigration of highly skilled individuals can easily harm less affluent nations. Once again, studying the relationship between foreign born medical professionals and health measures allows for better understanding of the benefits and drawbacks of policies that invite immigrant medical professionals. The conclusions from this research paper as well as the other papers on this topic provide implications for how to balance the risk of harm towards less affluent nations when importing highly-skilled medical labor into the United States.

Regarding domestic literature on the primary care shortage, there have been many proposed health reforms to combat this scarcity. These include increases in payment to primary care practitioners, specific community health teams, grants to primary care programs, increased support of primary care residency positions, scholarships or loan forgiveness to medical students pursuing primary care (Carrier, Yee, & Stark, 2011). However, even in states that have implemented these policies, such as Massachusetts, primary care physicians are still at a supply shortage with patients facing ever longer waiting time for appointments. Moreover, only a third of new US physicians pursue primary care, a low percentage when considering that primary physicians treat most of the United States and the small number of medical school graduates (Schwartz, 2012). These conflicting conclusions indicate that there is more to the solution than simply increasing pay for primary care medical professionals.

In conjunction to the already stated reforms, studies have shown that improvements towards health information technology (HIT) must be implemented to have tangible benefits for patients. Unfortunately, the realization of improved HIT is a long-term, slow process and inter-related with diminishing primary care medical labor. The equivalent to roads in public infrastructure, HIT is essential for primary care practitioners to be productive and effectively perform their jobs (Bodenheimer, Grumbach, & Berenson, 2009). This technology is necessary for efficient information flow between the different health delivery locations, from inpatient to outpatient, and EMS settings. Without patient information, medical professionals are unable to take full advantage of their time and administer the necessary treatments. These improvements in HIT extend far beyond simply improving patient records; they also improve medical services through scheduling appointments and reaching patients in more inaccessible locations and when consulting with other physicians for another opinion. With the current workload of primary care physicians higher than other specialities due to lack of necessary HIT improvements and increasing numbers of patients as fewer and fewer medical students choose primary care, the number of primary care practitioners falls ever lower. These studies in medical professional shortages illustrate that the primary care shortage in the United States is complicated, with the solution needing multiple interventions in various levels of medical service. There is no simple, quick solution to ensure that current patients do not receive worse care as these solutions are slowly implemented into the existing healthcare system.

However, most studies on the shortage of primary care do not study the effects of foreign-born medical professionals. Although foreign-born medical professionals may not be the long-term solution to the scarcity, they may be an essential stop-gap for current citizens to maintain their health while more structural reforms take place. In the few papers studying the effects of immigration on the host country, Furtado & Ortega, 2020, analyzed the effects of foreign born nurses on the quality of nursing homes. They did this by measuring the number of falls from each nursing home and finding the share of foreign born medical professionals of the commuting zone in which each nursing home was located (Furtado & Ortega, 2020). Estimating a time fixed effects and nursing home fixed effects model, they found that there was a significant negative relationship between the number of falls and the share of the foreign born nursing population. With greater numbers of foreign born nurses, there were fewer falls in those nursing homes. This result is encouraging, indicating that the short-term solution of foreign born medical professionals may be effective. Therefore, although the literature has studied the impact of immigrant nurses on nursing homes and the effects of brain from leaving immigrant populations, the literature failed to study the effect of different medical professionals on measures of health for all citizens, in both hospitals and out-patient facilities, which is what this paper endeavors to accomplish. Due to the previous research on a similar topic, this paper hypothesizes that increasing the number of foreign medical professionals will improve the health measures. This hypothesis is further bolstered when considering the training of foreign-born nurses. In many studies, there have been indications that foreign-born nurses are better trained than local nurses due to a positive selection mechanism in their host countries. This relationship is likely due to foreign nurses needing to pass qualification exams in both their host countries and the countries to which they immigrate.

The results of this research is essential since the literature indicates that the immigration of foreign professionals is not a sustainable solution. If there is no benefit towards the immigration of medical professionals, there is real risk of harm towards the healthcare systems of other countries. Research on this topic can also prime government agencies for the restructuring of healthcare policies to ensure that the healthcare system does not depend entirely on foreign labor in the long run, instead pairing immigration policy with health policy.

3 Data

For the data, I am using the National Health Interview Survey (NHIS) from the years of 1997 to 2018. This cross-sectional survey is used to gather information regarding the health of the US population and is suitably representative of the population of the United States. The other dataset I will be using is the Current Population Survey (CPS) that conducts monthly surveys to better understand the labor market. Similarly, this dataset uses a repeated cross-sectional survey. These data sets were chosen for their specificity regarding the location of survey respondents; the NHIS gave the MSA as well as regional data for the respondents. The CPS gave the metropolitan locations as well as the state locations of its participants. Since both of these surveys are repeated cross-sections, the higher specificity allows for an aggregated fixed effects analysis where the unit observation can be either a MSA or a region.

Regarding the NHIS data set, their questionnaire provided information on the health statuses of the respondents, including data on chronic and regular measurements of health such as the measurements of asthma, diabetes, and self-reported ratings on well-being. This allows for analysis of the effect of foreign-born medical professionals in both short-term and the long-term health measures. In contrast, the CPS data has detailed information regarding the professionals themselves, including measures of quality of the workers themselves that can serve as control variables.

3.1 Variable Construction and Data Trends

The level of foreign-born medical professionals variable takes into account the population of the region or MSA and calculates the foreign-born medical professionals per capita. This is because, when considering factors that may impact the relationship between foreign-born medical professionals and the health measures, the effects of population size must be accounted for. Regarding the population level, consider a physician treating one thousand patients versus one treating two thousand patients. It would be unsurprising for the physician with fewer cases to provide better care.

Subsequently, this variable is constructed by dividing the total number of foreign-born medical professionals in region r and time t by the population of all people in the region r and year t (population values were counted from the NHIS data set as it is a nationally representative sample) to facilitate a fixed effects model. By dividing the total number of foreign-born medical professionals by the total population in the same region and year, this per capita variable accounts for the possibility that a larger population tends towards poorer health indicator values because of the inability of health care professionals to take care of all patients with the necessary amount of attention.

In addition to the population levels, the local population of natively born medical professionals must also be contained within the model. The health outcomes of the population are determined by both the natively and foreign-born medical professionals, and to disentangle these relationships, the effects of the natively born medical professionals, similarly adjusted for the population level, must be included in the regression.

Furthermore, once the not-in-universe and under eighteen year-old observations are dropped, each measure of health: BMI, asthma, self-rated health status, and diabetes are averaged across region or MSA for each year. For example, the asthma variable is calculated by assigning each participant who had asthma a value of one and each participant who did not have asthma a value of zero. The average of these values across the region or MSA is then used as a possible measure of health. Similar techniques are used with other medical care indicator variables:

self-rated health, BMI, diabetes, and asthma.

Finally, control variables of age, education level, gender, whether the individual lived below the poverty threshold, and whether the patient was foreign born are identified as likely to have strong relationships with the chosen health measures. These control variables, such as education, are also constructed similarly as the medical care variables, with education having a scale from one to five that goes from without a high school education to obtaining a graduate degree. The percentage of individuals falling in each category are found for each region or MSA for the regressions. Then, the averaging process as explained for the health measures is utilized for the control variables of gender, age, poverty, and whether the patient was foreign-born.

To obtain visualization of trends in the data, a series of graphs were constructed to examine the time trend of various health measures and the share of medical professionals nationally and regionally. In Figure 1, which compares the time trends of the self-reported health ratings from participants in the NHIS against the share of foreign health professionals, there seems to be a negative correlation, especially in years from 1996 to 2002. To see which regions were driving these movements in the data, the time trend for foreign-born and health ratings were then separated into regional graphs (Figure 2). In this figure, it seems the late 1990's to early 2000's saw opposite trends, but the later 2010 decade saw a more similar trend between health ratings and number of foreign-born professionals with the Midwest and the South showing this behavior most clearly.

Examining other indicators of health such as values of BMI and incident rates of anemia, arthritis, and diabetes, it seems that the trends of diabetes and arthritis were most similar to that of the share of foreign-born health professionals (Figure 3 and Figure 4). For Figure 5, the relationship was much less clear, with trends running together some years and running in opposite directions in other years. The trends are similar from 1995 to 2000 but begin diverging after from 2005 to 2010.

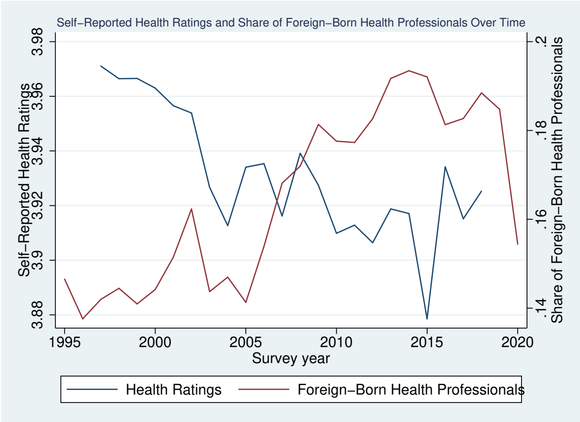

Figure 1: Health Ratings and Foreign Medical Workforce Time Trends

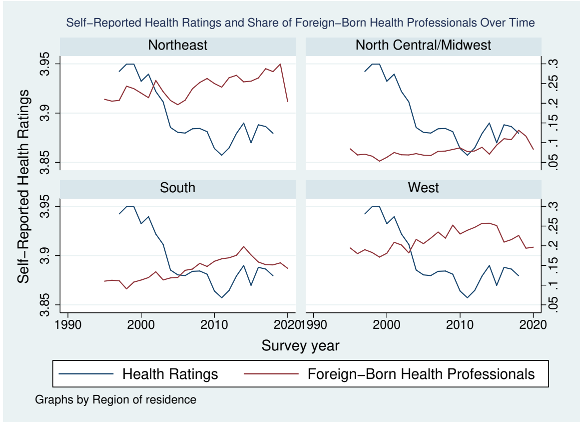

Figure 2: Health Ratings and Foreign Medical Workforce Separated by Region

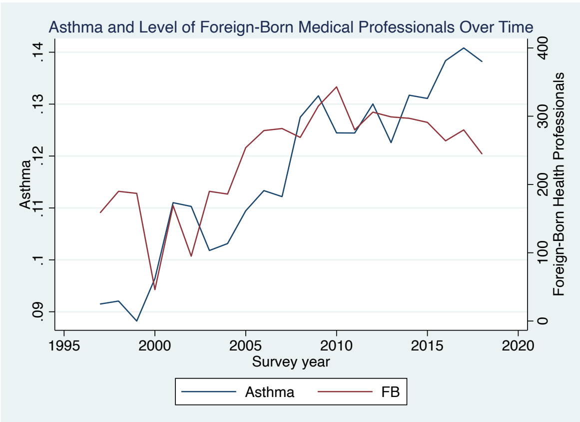

Figure 3: Asthma and Share of Foreign Born Health Professional Time Trends

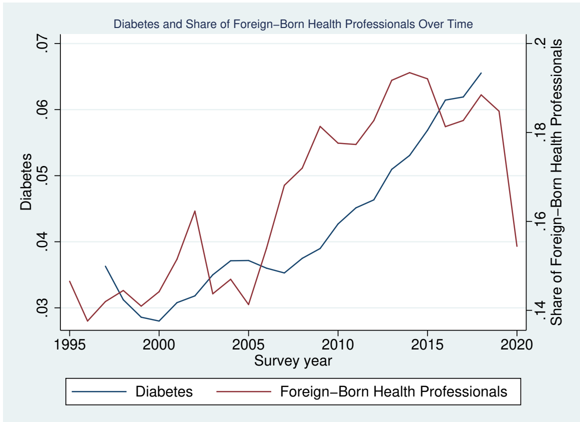

Figure 4: Diabetes and Share of Foreign Born Health Professional Time Trends

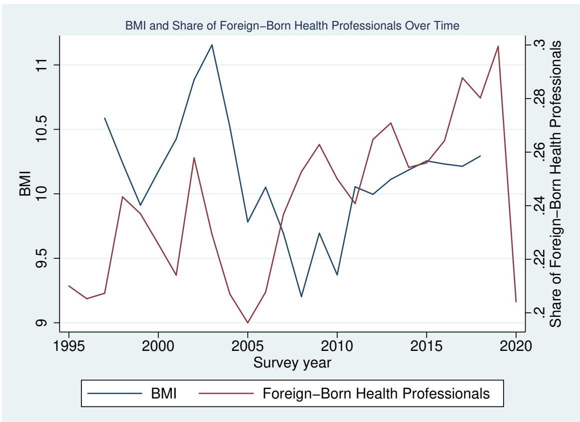

Figure 5: BMI and Share of Foreign Born Health Professional Time Trends

3.2 Summary Statistics

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Age	47.866	18.109	18	85	663814
Female	0.559	0.497	0	1	663814
Educational attainment	3.659	1.317	1	5	663814
Did not finish high school (1)	.	.	.	.	116027 (0.175)
Finished high school (2)	.	.	.	.	181039 (0.273)
Did not finish college (3)	.	.	.	.	195000 (0.294)
Finished college (4)	.	.	.	.	111038 (0.167)
Obtained higher degrees (5)	.	.	.	.	60710 (0.091)
Born in foreign country	.159	.366	0	1	663814
Below poverty threshold	.161	.366	0	1	663814
Self-Rated health status	3.689	1.087	1	5	663814
Ever told had asthma	0.115	0.319	0	1	663814
Body mass index	30.018	14.843	6.600	99.990	663814
Ever told had diabetes	0.094	0.285	0	1	663814

Table 2: Region Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Age	47.989	1.915	44.463	53.21	88
Female	0.559	0.014	0.531	0.591	88
Did not finished high school	0.17	0.043	0.087	0.255	88
Finished high school	0.274	0.034	0.205	0.333	88
Did not finish college	0.292	0.03	0.231	0.342	88
Finished college	0.17	0.024	0.129	0.245	88
Obtained higher education degree	0.094	0.022	0.064	0.157	88
Born in foreign country	0.156	0.0424	0.142	0.178	88
Below poverty threshold	0.16	0.0324	0.14	0.181	88
Self-rated health status	3.699	0.059	3.562	3.805	88
Asthma	0.117	0.018	0.08	0.152	88
BMI	30.073	0.823	28.039	31.672	88
Diabetes	0.093	0.022	0.052	0.146	88

The summary statistics table can be broken into two sections, variables that are indicators of health and control variables. The four health indicators are BMI, asthma, diabetes, and self reported health variables. The low mean values for asthma and diabetes indicate that the participants in the NHIS are generally free of these chronic conditions, matching the prevalence rates given by the CDC. Similarly, the BMI mean value also agrees with much of the CDC's data on the average BMI of the United States.

As for the control variables, age, gender, education level, whether the individual lives below the poverty threshold, and whether the patient is foreign-born, the average age of the participant is forty-eight years old with the majority of participants also being women. In terms of education, most of the participants have finished high school (the percentage of the total

Table 3: MSA Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Age	45.75	2.561	39.314	51.958	280
Sex	0.567	0.043	0.397	0.717	280
Did not finished high school	0.186	0.065	0.047	0.418	280
Finished high school	0.275	0.058	0.122	0.477	280
Did not finish college	0.284	0.047	0.18	0.462	280
Finished college	0.168	0.047	0.064	0.364	280
Obtained higher education degree	0.086	0.032	0.013	0.204	280
Born in foreign country	0.152	0.031	0.078	0.273	280
Below poverty threshold	0.155	0.051	0.090	0.454	280
Self-Rated health status	3.821	0.138	3.377	4.186	280
Asthma	0.095	0.027	0.023	0.182	280
BMI	29.259	2.72	25.231	47.031	280
Diabetes	0.061	0.02	0.022	0.141	280

population is noted in the parentheses next to the sample size). Moreover, unsurprisingly, most of the individuals are born in the United States and live above the poverty threshold.

Table 2 and 3 are the summary statistics for the two different specifications, regional level and MSA-level as the number of observations change due to aggregation. Note that the mean and the standard deviation are similar between the original dataset and the two specifications.

4 Empirical Model

In considering the methodology for this research question, a fixed effects model will be utilized. Furthermore, since the data is in the form of a repeated cross-sectional survey, I aggregated the data across region or metropolitan statistical areas (MSA's) when this information is available. This aggregation is necessary because this dataset is cross-sectional, a typical fixed effects model with respect to the individual participant is not possible. Bias would be introduced as the participants surveyed change every year, eliminating the possibility of controlling for unobserved, persistent individual factors . When the model is implemented with aggregation, the number of observations decrease, but the fixed effects model can eliminate the omitted variable bias that appears in other models, such as ordinary least squares (OLS).

This reduction in omitted variable bias is due to the key assumption of OLS being the exogeneity of regressors, or that regressor values are determined outside of the model, to allow the error term to be uncorrelated with independent variables. For this assumption to not be violated, any variable that could impact the dependent variable and vary with other regressors must be included in the model. However, in investigating the relationship between immigration and health measures, identifying and finding data to operationalize all variables that satisfy those two qualities is near impossible. From HIPPA regulations to the difficulty in understanding the specific mechanisms between these two variables, an OLS regression is unlikely to result in an unbiased conclusion. In contrast, the fixed effects model utilized in this paper accounts for many of those omitted variables by controlling for unchanging effects.

Furthermore, endogeneity problems common in research regarding immigration. This endogeneity is common because most immigrants move due to factors such as economic opportunity or social networks. Unfortunately, both of these variables are likely to affect the dependent variable of various health measures while being difficult to operationalize and measure. Moreover, if endogeneity persists in the regressions, it can result in erroneous conclusions with instances of reverse causality. In the context of this research question, reverse causality would result in regressions demonstrating that health outcomes are worse in locations with more foreign-born medical professionals. However, this might result from health professionals moving to locations with worse health outcomes. Especially for minority physicians in the United States, studies have shown that they are more likely to work in communities with worse outcomes and care for these communities in primary care settings (Walker, Moreno, & Grumbach, 2012). In fact, even for local physicians, they value "community appeal and a challenging practice" as the two most important considerations of where they choose to live and work, indicating that communities with worse health outcomes may attract physicians who seek challenges in their work (Kazanjian & Pagliccia, 1996).

Thus, this paper uses multiple means to reduce endogeneity. The first method will use a fixed effects model to analyze data from 1997 to 2018, using the census region every year as the unit of observation. Since this dataset encompasses twenty years, lags are one solution to reduce endogeneity. These lags describe regressions where the foreign-born medical professionals variable is lagged years behind the health measure variable. These lagged regressions take advantage of the assumption that endogeneity between medical variables and lagged foreign born medical populations decreases. This assumption is made because the confounding factors in time t that affect both health outcomes and the levels foreign born medical populations in time t is likely to have a reduced correlation with the levels foreign born medical populations in time $t-1$. Moreover, the lags may be able to capture the time lag between the effect of foreign born professionals on measurable differences for the chosen health measures. In measurements of the incidence rates of these chronic conditions, it would be highly unlikely that an increased foreign-born population in year t would reduce the share of the population that suffered from diabetes or asthma in the same year t. Rather, the effects of immigrant medical professionals may only be felt years after.

Thus, the model for these lagged regression is shown below:

$$HM_{r,t} = \beta_1 FB_{r,t-k} + \beta_2 Local_{r,t-k} + \beta_3 X_{r,t} + \gamma_r + \lambda_t + u_{r,t}; k = 0, 5. \tag{1}$$

The model above describes the regressions, where HM refers to the various health measures including self-assessed health quality, asthma, BMI, and diabetes of census region r at time t. The independent variable is denoted as FB or a measure of the share of foreign born medical professionals in region r at time t. X is a matrix of the control variables related to the census region including the educational attainment, age, gender, whether the individual lives below the poverty threshold, and whether the patient is foreign-born as discussed in the data section. The fixed effects are seen in the λ term and the γ term where the λ term refers to yearly fixed effects, while the γ term refers to regional fixed effects. Finally, k describes the number of years the number foreign-born medical professionals is lagged behind.

The second method to reduce endogeneity uses a different model, studying a different time duration. Due to the increased geographic specificity during 1997-2001, a different unit of observation, the Metropolitan Statistical Areas (MSA), is used. However, since this dataset only goes from 1997-2001, lags can not be implemented. Thus, instead of lags, instrumental variables are used. An instrumental variable that is directly related to the number of foreign-born medical professionals while being uncorrelated to today's health measure is necessary.

To construct an instrumental variable that can satisfy those two requirements, a common solution in previous immigration studies is to utilize historical information to predict present-day immigration locations. This solution is based on evidence demonstrating that ethnic enclaves, a geographic location with high concentrations of immigrants from the same ethnic identity, strongly influence the migration locations of immigrants, with newly arrived individuals moving to geographic locations with a sustained immigrant population. Applying this to immigrant medical professionals as they are likely to behave similarly to other immigrants and move to locations with high concentrations of individuals from the same ethnic group, an instrumental variable constructed from historical migration patterns is expected to be correlated with the right-hand side variable.

A specific instrumental variable that takes advantage of this relationship is the shift-share variable, which predicts the share of foreign-born medical professionals (shown below). The first term in the numerator is the share of foreign-born medical professionals in each MSA z in 1970 while the second term refers to the number of immigrants from country b in the present day, and the denominator refers to the total number of immigrants in MSA z currently. Referencing equation 2, this formulation predicts the foreign-born share within each MSA z and period t. It does this by finding the share of individuals from country b within each MSA z in the 1970's and using the total number of immigrants in the United States from country b at time t to predict the number of foreign born from country b in each MSA at time t. By summing over all of the countries, the formulation results in a term that predicts the number of foreign born individuals in each MSA at time t. Finally, this total number of predicted foreign born is divided by the population of all people in MSA z and time t to find the foreign-born share term. This foreign-born share term can be then used as an instrumental variable for the share of foreign born medical professionals when assuming that medical professionals are a constant fraction of the total immigrant population.

The shift-share variable used to instrument the share of foreign born medical professionals in MSA z is written below:

$$INST_{FB,zt} = \left(\sum_b \frac{N^b_{z,1970}}{N^b_{1970}} N^b_t \right) / N_{zt} \tag{2}$$

Furthermore, reverse causality could also apply for local medical professionals as for the same reasons outlined earlier. Thus, another instrumental variable for the local physician population is created to address the this issue. Two formulations are tested for the local instrumental variable: a population growth construction and a variation on the shift-share instrumental variable used for the foreign-born population. The population growth variable for local populations is shown below:

$$INST_{Local,zt} = \frac{Pop_{z,1970}(1+r)^{t-1970}}{N_{zt}} \tag{3}$$

, uses a population growth model to predict the number of local medical professionals given the population in the 1970's. This construction assumes that the local population of medical professionals is correlated with the population of individuals in MSA z in 1970, by the population growth rate represented by r in the model. To find the share of the population that are foreign-born medical professionals, the numerator is divided by the population in MSA z at time t. For the sake of a fixed effects model, this formulation of a local instrumental variable varies with time and MSA.

Regarding the validity of this formulation of the population growth local instrumental variable, it has to also satisfy the two conditions discussed above. The local IV should not be correlated with the values of the health measures of the time period studied but should be correlated to the level of local medical professionals. Using a similar argument to the one used for $IV_{FB,zt}$, the local instrumental variable should not be related to the health measures in the time period studied as the settlement patterns of physicians thirty years ago should have no correlation with the health of individuals in the time period of 1997-2001. For the second qualification of an instrumental variable, the local IV should be related to the local per capita value for local physicians in MSA z and time t as the number of physicians should increase at a similar rate to the rate of population increase in the United States.

The second local instrumental variable is shown below:

$$INST_{local,zt} = \frac{N_{z,1970}^{local}}{N_{1970}^{local}} * N_t^{local}/N_{zt}. \tag{4}$$

The equation above finds the share of local born individuals in MSA z in 1970 and multiplies the share by the total local population in time t to find the predicted number of local individuals in MSA z in time t. By dividing by the total population in MSA z and time t, the predicted share of local born in MSA z and time t is found. Similarly, assuming that medical professionals account for a fraction of the total local population, this instrumental variable can be used as a measure of the local born medical professional population. This shift-share local instrumental variable assumes that the settlement patterns of the local individuals in the 1970's are correlated with the settlement of local individuals in 1997-2001, which is a plausible assumption when considering abundance of resources near childhood homes and support networks that would encourage individuals to stay near their hometowns. Additionally, once again, the settlement patterns of people in the 1970's are unlikely to have any correlation to the medical care of patients from 1997-2001.

Subsequently, the model for this second, truncated dataset is shown:

$$HM_{z,t} = \beta_1 FB_{z,t} + \beta_2 Local_{z,t} + \beta_3 X_{z,t} + \gamma_z + \lambda_t + u_{z,t}. \tag{5}$$

In this model, HM refers to the health measures of z, a Metropolitan Statistical Area (MSA) at time t. The independent variable is again denoted as FB or the instrumented share of foreign born medical professionals in MSA z at time t. The X is a matrix of the control variables related to the MSA at time t, including the instrumented local medical professional population. The λ term refers to the yearly fixed effects, and the γ refers to MSA-level fixed effects as before.

As a final note, although, there have been issues regarding the predictive power of the shift-share instrumental variable in recent years due to immigrants settling in locations without pre-existing ethnic enclaves, there have been inconsistent results with other instrumental variables that attempt to solve the same problems with endogeneity in immigration research (Jaeger, Ruist, & Stuhler, 2018). As a result, I will continue to use the shift-share instrumental variable in this paper.

5 Results

5.1 Region

A preliminary regression was run on the health indicator variables using yearly and regionally fixed effects but no control matrix. The fixed effects, as mentioned previously, should take into account any omitted variables that are fixed over time such as unchanging differences between regions (Northeast, Midwest, South, and West). None of the chosen medical indicators have significant coefficients, which is unsurprising given the lack of controls and means to reduce endogeneity; it is almost certain that the coefficient estimates are biased. Moreover, although for many of the indicators such as self-rated health status, BMI, and asthma, the coefficients are in the opposite direction as hypothesized, but the standard errors (clustered by region) indicate that these relationships are insignificant (Appendix: Table 13).

The preliminary regression motivates the next regression (Table 4) ; the next analysis conducts a regression with the control variables discussed in the data section: age, share of female participants, the different levels of educational attainment, whether the patients were immigrants themselves, and the percentage of the individuals in the region living below the poverty threshold while using the per capita formulation of the foreign-born medical professionals variable. Regarding the results, this regression similar reports no significant coefficients. However, instead of agreeing with the existing literature where increased foreign-born medical professionals increase the values of health measures, this regression implies that a negative relationship exists between the level of foreign-born medical professionals and the health status of the population. Some health measures do report coefficients in the expected direction (asthma) with higher levels of foreign-born medical professionals resulting in better values for health measures. Nonetheless, the results of this regression most likely have issues with endogeneity as the local medical labor population has an insignificant relationship with many of the health measure variables (the exception being self-rated health). These insignificant relationships are counter-intuitive, as more medical labor is likely to result in better care. The most important takeaway from this regression, however, are the significant coefficients with respect to some of the control variables such as a few levels of educational attainment and age. These results suggest that the chosen control variables are related health outcomes as hypothesized, and thus, these control variables are included in the following regressions.

Since endogeneity likely remains, the next set of regressions report the results of the lagged models. Beginning with the self-rated health variable (Table 5), the regressions demonstrate insignificant relationships with the level of foreign-born medical professionals for all lags. At first glance, the negative result of Table 4 disappears, implying that the results from the previous regressions were not robust. Examining more closely, the first two lags report positive coefficients, the expected direction of the regression, while the others report a negative relationship. In addition, the results from the BMI lagged regressions (Table 6) have a significant negative relationship with lag one at the 10% level. This significant relationship does not persist through lag two and three, but their coefficients are in the expected direction–more foreign medical professionals resulting in lower BMI. In contrast, the fourth and fifth lag reflect a positive relationship. Moving to the lagged regressions for asthma (Table 7), these regressions also report a significant coefficient at the 10% level for lag one. Another interesting note for the asthma lagged regressions is that it reflects the same pattern as all the other indicator variables. The first two lags of the regression has the coefficient in the expected direction. However, the rest have the opposite sign with lag four have a significant, positive relationship with the right hand side variable at the 1% level. Finally, for diabetes (Table 8), there is a significant, negative coefficient at lag two at the 5% significance level but also a positive, significant relationship at the 10% level at lag four, reflecting the same patterns as the other health measures.

Table 4: Regional Preliminary Regression

	(1)	(2)	(3)	(4)
	Self-rated health status	BMI	Asthma	Diabetes
FB per capita	-1.410	41.26	-1.002	0.493
	(1.748)	(86.92)	(0.757)	(1.028)
Local per capita	1.297***	48.57	0.00762	0.790
	(0.182)	(28.85)	(0.761)	(0.374)
Below poverty threshold	-0.551*	-2.276	0.175	-0.0729
	(0.233)	(6.205)	(0.142)	(0.0636)
Not born in the United States	-0.215*	5.035	-0.0553	0.141***
	(0.0730)	(6.101)	(0.0674)	(0.0211)
Age	-0.0288***	0.0176	-0.000443	0.00487*
	(0.00278)	(0.138)	(0.00163)	(0.00173)
Sex	-0.201	10.37	0.108***	0.103
	(0.181)	(9.583)	(0.0173)	(0.0708)
Did not finish high school	-0.246	21.12	-0.0220	0.0631
	(0.396)	(12.59)	(0.405)	(0.199)
Finished high school	-0.454	-3.168	-0.00751	0.0847
	(0.261)	(7.165)	(0.187)	(0.117)
Did not finish college	0.255	-6.867	-0.00949	-0.0817
	(0.361)	(13.18)	(0.0911)	(0.103)
Finished college	0.542	-0.122	0.149	-0.0450
	(0.392)	(9.234)	(0.279)	(0.143)
Obtained higher education degree	0.940	-13.36	0.133	-0.0333
	(0.433)	(13.08)	(0.258)	(0.150)
Constant	5.265***	21.26	0.0240	-0.263
	(0.188)	(18.22)	(0.196)	(0.139)
Observations	88	88	88	88

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Standard errors in parentheses (clustered at the region). Control variables included with yearly and regional fixed effects.

Table 5: Lagged Self-Rated Health Regressions

	(1) Health	(2) Health	(3) Health	(4) Health	(5) Health
FB Capita Lag 1	7.006				
	(4.867)				
Local Capita Lag 1	0.217				
	(3.659)				
FB Capita Lag 2		4.200			
		(3.364)			
Local Capita Lag 2		-0.100			
		(2.481)			
FB Capita Lag 3			-2.663		
			(3.226)		
Local Capita Lag 3			-1.372		
			(1.573)		
FB Capita Lag 4				-2.101	
				(4.711)	
Local Capita Lag 4				-3.423	
				(1.663)	
FB Capita Lag 5					-0.195
					(4.993)
Local Capita Lag 5					-3.040*
					(1.135)
Constant	4.699***	4.769***	4.799***	4.901***	4.961***
	(0.0956)	(0.175)	(0.138)	(0.115)	(0.306)
Observations	84	80	76	72	68

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Standard errors in parentheses (clustered at the region). Control variables included with yearly and regional fixed effects.

Table 6: Lagged BMI Regressions

	(1) BMI	(2) BMI	(3) BMI	(4) BMI	(5) BMI
FB Capita Lag 1	-219.7*				
	(84.85)				
Local Capita Lag 1	72.44				
	(54.14)				
FB Capita Lag 2		-254.1			
		(172.7)			
Local Capita Lag 2		44.48			
		(78.30)			
FB Capita Lag 3			-92.88		
			(168.0)		
Local Capita Lag 3			12.11		
			(47.65)		
FB Capita Lag 4				1.632	
				(78.89)	
Local Capita Lag 4				37.26	
				(58.63)	
FB Capita Lag 5					154.6
					(188.8)
Local Capita Lag 5					147.5
					(66.53)
Constant	28.08	29.19	33.66	29.33	20.06
	(16.17)	(16.03)	(17.74)	(17.43)	(12.52)
Observations	84	80	76	72	68

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Standard errors in parentheses (clustered at the region). Control variables included with yearly and regional fixed effects.

Table 7: Lagged Asthma Regressions

	(1)	(2)	(3)	(4)	(5)
	Asthma	Asthma	Asthma	Asthma	Asthma
FB Capita Lag 1	-4.295*				
	(1.388)				
Local Capita Lag 1	-1.551				
	(1.014)				
FB Capita Lag 2		-1.474			
		(0.700)			
Local Capita Lag 2		-0.697			
		(0.702)			
FB Capita Lag 3			1.551		
			(0.670)		
Local Capita Lag 3			-0.425		
			(1.224)		
FB Capita Lag 4				7.484***	
				(0.872)	
Local Capita Lag 4				0.777	
				(0.492)	
FB Capita Lag 5					3.100
					(3.290)
Local Capita Lag 5					-2.069
					(1.249)
Constant	0.212	0.157	0.190*	0.134	0.340*
	(0.131)	(0.0930)	(0.0632)	(0.0624)	(0.128)
Observations	84	80	76	72	68

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Standard errors in parentheses (clustered at the region). Control variables included with yearly and regional fixed effects.

Table 8: Lagged Diabetes Regressions

	(1)	(2)	(3)	(4)	(5)
	Diabetes	Diabetes	Diabetes	Diabetes	Diabetes
FB Capita Lag 1	-1.978				
	(1.148)				
Local Capita Lag 1	0.266				
	(0.442)				
FB Capita Lag 2		-2.872^{**}			
		(0.545)			
Local Capita Lag 2		-0.599			
		(0.492)			
FB Capita Lag 3			0.243		
			(1.431)		
Local Capita Lag 3			-0.595		
			(0.372)		
FB Capita Lag 4				2.315^{*}	
				(0.746)	
Local Capita Lag 4				-0.570	
				(0.941)	
FB Capita Lag 5					3.376
					(1.493)
Local Capita Lag 5					0.614
					(0.413)
Constant	-0.116	-0.129	0.00417	-0.0363	-0.0808
	(0.148)	(0.120)	(0.130)	(0.0588)	(0.141)
Observations	84	80	76	72	68

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Standard errors in parentheses (clustered at the region). Control variables included with yearly and regional fixed effects.

The combination of the population level effect, inclusion of the local population of medical professionals, and the lagged effects from chronic conditions demonstrate that the level of foreign-born medical professionals may positively impact health outcomes for the population. All of the health measures have coefficients in the expected direction for the first two to three lags. However, further analysis is necessary as this direction does not persist through all of the lags. It is unclear as to whether the time window for a meaningful effect is only two to three years, whether endogeneity remains in the dataset, or if there is an insignificant relationship between foreign-born and the chosen health measures.

5.2 MSA

Since the data was collected in a cross-sectional survey, as mentioned before, the results were aggregated for a fixed effects model. For most of the years, the data could only be aggregated across regions, of which there are only four. Therefore, there were only eighty-eight observations for over twenty years of data. However, for five years (1997-2001), there is available data at the metropolitan statistical area (MSA) level. Since the dataset has approximately fifty MSA's every year, this would increase the number of observations by more than three-fold. This increased specificity in a small portion of the data allowed for another set of regression to better understand the relationship between foreign-born medical professionals and health outcomes.

Table 9 shows that none of the medical indicators have significant relationships with the level of foreign-born medical professionals. Self-rated health status and diabetes have coefficients in the hypothesized directions, but the indicators of BMI and asthma do not. Once again, since there are significant relationships between the health measures and control variables, these variables were included in the rest of the analysis with the MSA-level data.

Table 9: MSA Preliminary Regression

	(1)	(2)	(3)	(4)
	Self-Rated Health status	BMI	Asthma	Diabetes
FB per capita	2.257	52.51	0.261	-0.545
	(3.122)	(93.74)	(0.934)	(0.558)
Local per capita	0.474	-29.28	0.0304	-0.127
	(1.418)	(41.12)	(0.329)	(0.301)
Below poverty threshold	-0.00189	-3.180	0.0107	0.0151
	(0.111)	(3.576)	(0.0234)	(0.0172)
Not born in the US	0.0146	2.547	-0.0106	-0.00663
	(0.178)	(2.587)	(0.0399)	(0.0237)
Age	-0.0183***	0.00194	0.000146	0.00246*
	(0.00603)	(0.145)	(0.00144)	(0.00123)
Female	-0.00138	4.118	0.0168	0.00679
	(0.275)	(5.982)	(0.0496)	(0.0370)
Did not finish high school	0.480	-8.167	0.0687	-0.164**
	(0.443)	(8.388)	(0.118)	(0.0819)
Finished high school	0.504	-4.810	0.124	-0.158**
	(0.356)	(8.104)	(0.103)	(0.0753)
Did not finish college	0.652	-7.128	0.222**	-0.0990
	(0.421)	(10.49)	(0.106)	(0.0845)
Finished college	1.149**	-6.905	0.0936	-0.139
	(0.437)	(10.27)	(0.115)	(0.0985)
Obtained higher education degree	0.779	-9.288	0.187	-0.114
	(0.494)	(11.80)	(0.122)	(0.0907)
Constant	4.123***	31.40***	-0.0900	0.0567
	(0.433)	(8.771)	(0.106)	(0.0873)
Observations	279	279	279	279

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Standard errors in parentheses (clustered at the MSA). Control variables included with yearly and MSA-level fixed effects.

5.3 Foreign-Born Instrumental Variable

When testing the first stage regression of the shift-share instrumental variable, the coefficient is significant at the 5% level. However, Table 14 in the Appendix shows that this relationship is unexpectedly negative. This negative relationship indicates that the levels of foreign-born individuals in the 1970's of each MSA are negatively correlated with levels of foreign-born medical professionals in the time period studied of each MSA. This result seemingly contradicts the assumption that ethnic enclaves have an effect on where immigrants settle and has predictive power. However, another possible explanation may be that the movements of foreign-born medical labor do not follow the settlement patterns of the general population of immigrants. With the data available, it is difficult to conclude which of these two options is the case.

Furthermore, the F-stat for this instrumental variable is 4.389, which implies that it is weak. However, given the limited dataset, this shift-share instrumental variable is likely the best proxy for the level of foreign-born medical professionals. For future research, more analysis should be conducted to closely examine the unexpected direction of the first stage regression between the level of foreign-born medical professionals and the shift-share instrumental variable. Moreover, future researchers should also investigate whether another instrumental variable might be better correlated with the right hand side variable.

Nonetheless, the significant coefficient indicates that the shift-share instrumental variable is correlated with the foreign-born medical professionals per capita and thus, this instrumental variable for the share of foreign born medical professionals is used for regressions against the health measures.

5.4 Robustness: Local Instrumental Variable

The first stage regression for the growth local instrumental variable is as expected with a coefficient in the positive direction, significant at the 1% level with an F-stat of 15.90 (Appendix: Table 15). Due to the encouraging first stage regression results, the growth local and shift-share foreign-born instrumental variables are used for the regressions in Table 10. The regressions demonstrate insignificant results for all for health outcome variables. While the direction for self-rated health and BMI are in the opposite direction, the coefficient direction for asthma and diabetes are as expected.

As a robustness check, a shift-share version of the local instrumental variable is also tested. The first stage regression also reports a coefficient in the expected direction at a 1% significance level with an F-stat of 11.90 (Appendix: Table 16). The regression results for the shift-share instrumental variable are similar to the growth instrumental variable, all of the coefficients are insignificant. However, the sign of the self-rated health rating became positive in the shift-share local instrumental variable regression (Table 11).

Since the growth variable reports a higher correlation to the local medical labor population per capita, the next series of regressions will use the first local instrumental variable. As for the coefficients associated with foreign-born variables, the similarly insignificant coefficients between the values for both the growth local variable and the shift-share local variable are encouraging towards the robustness of the results.

More robustness checks were conducted when examining the results of the previous regression. Taking into account the instances where there were no foreign-born medical professionals in the MSA or when the population of the MSA was too small for changes in foreign-born medical professionals to induce any changes in the health measure values, conditions are applied to the dataset. This is done by first imposing a ratio of foreign-born to local of at least 0.05 to ensure that the model only included observations where there were foreign-born medical professionals in the MSA. Secondly, different sample population conditions are imposed, ranging from at least 200 to at least 500 to 1000. These population conditions are imposed for power and to ensure that an increase in medical professionals would actually have effects. One could imagine that a MSA with a small enough population may not need more medical professionals to improve care. The regression for a ratio of 0.05 and population condition of 500 is shown in Table 12 is shown. Although the sign for BMI flipped, all of the results remain insignificant as before. The other robustness checks are shown in further detail in the Appendix (Tables 17, 18, 19, 20, and 21), with other population conditions and other limits on the foreign born to local born ratio. Ultimately, the signs between different conditions and health measures, but none of the regressions have significant values. Thus, this paper concludes that given the dataset and all of the available means to remove as much as endogeneity as possible, the number of foreign-born medical professionals has no effect on health measures: BMI, self-rated health, incidence of asthma, and incidence of diabetes.

Table 10: Foreign IV and Growth Local IV

	(1)	(2)	(3)	(4)
	Self-Rated Health status	BMI	Asthma	Diabetes
FB per capita	-64.24	203.3	5.903	3.687
	(74.31)	(451.5)	(9.145)	(5.724)
Local per capita	29.18	-43.23	-1.710	-0.880
	(44.84)	(236.4)	(5.294)	(3.739)
Constant	5.970^{***}	22.09^{**}	0.0777	-0.120
	(2.069)	(8.946)	(0.242)	(0.153)
Observations	167	167	167	167

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Standard errors in parentheses (clustered at the MSA). Control variables included with yearly and MSA-level fixed effects.

Table 11: Foreign and Shift-Share Local IV

	(1)	(2)	(3)	(4)
	Self-Rated Health status	BMI	Asthma	Diabetes
FB per capita	89.64	20.63	-0.628	-0.589
	(552.2)	(1711.1)	(40.97)	(28.04)
Local per capita	-75.40	80.90	2.729	2.026
	(374.3)	(1118.8)	(27.92)	(18.90)
Constant	3.251	25.32	0.193	-0.0447
	(10.75)	(32.92)	(0.736)	(0.478)
Observations	167	167	167	167

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Standard errors in parentheses (clustered at the MSA). Control variables included with yearly and MSA-level fixed effects.

Table 12: Foreign IV and Shift-Share Local IV with Conditions

	(1)	(2)	(3)	(4)
	Self-Rated Health status	BMI	Asthma	Diabetes
FB per capita	-85.42	452.8	-8.886	7.283
	(128.8)	(1253.3)	(13.99)	(18.85)
Local per capita	-68.05	633.4	-4.620	9.855
	(130.2)	(1412.1)	(14.94)	(19.42)
Constant	3.862	29.87	0.139	0.113
	(3.806)	(33.68)	(0.334)	(0.490)
Observations	121	121	121	121

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Standard errors in parentheses (clustered at the MSA). Control variables included with yearly and MSA-level fixed effects. Conditions are: ratio at 0.05, population at 500)

6 Conclusions

This research paper investigates the question of whether the population of foreign-born medical professionals impact the health measures of the receiving country to fill a gap in the current literature regarding the effects of immigration on the receiving country. The analysis specifically studies both hospitals and out-patient facilities as well as different types of medical professionals ranging from physician's assistants to doctors. Generally, higher populations of medical professionals do not result in better health measures for citizens of the receiving country. For both the shorter time period and the longer time period analysis, they had generally insignificant relationships between the level of foreign-born medical professionals and the health measures: asthma, BMI, diabetes, and self-rated health.

These results have limitations, the most obvious of which are the amount of aggregation needed and the relatively short time period able to be analyzed. The small number of observations reduces the robustness of these results despite the methods taken to ensure that these conclusions remain even when assumptions are adjusted. Therefore, although data with more specific geographic information could not be found or obtained for this study, the possibility of more specific data spanning a longer time frame with panel data holds promise for future research in the same area. Moreover, many of the health measures available for this analysis change slowly and incrementally, which is difficult to see even in forty years. Medical conditions such as diabetes, BMI, and asthma are dependent on genetic pre-conditions. Any changes in the incidence rates of diabetes would be related to gene effects (which do not change in a few decades) as well as improvements in care. As for self-rated health status, this measure of health is imperfect as this variable has the ability to be highly volatile because it is directly dependent on the singular state of an individual at the time this question is answered. This randomness makes it difficult to find an overall relationship between the health measure and the right hand side variable. Hence, future analysis on this topic should attempt to focus on variables that are more directly related to medical care interventions and more responsive to changes in the level of foreign-born medical professionals.

The necessary improvements to reverse the primary care shortage will take decades to implement. While foreign medical professionals were promising as a short-term solution that prevents individuals from receiving inadequate care in the years before structural changes are implemented, these results suggest that this solution may not have large impacts on health outcomes. Therefore, when also considering the global network of affluent and less affluent countries and the negative ethical implications of poaching medical professionals from countries where they are highly needed, the lack of significant benefits from foreign labor must be weighed against these ethical implications. Ultimately, this paper suggests that foreign medical labor may not have a large enough effect on health outcomes to justify the human capital loss from growing, foreign economies.

7 Detailed Bibliography

References

Agrawal, A., Kapur, D., McHale, J., & Oettl, A. (2011, January). Brain drain or brain bank? The impact of skilled emigration on poor-country innovation. *Journal of Urban Economics*, *69*(1), 43–55. doi: 10.1016/j.jue.2010.06.003

Aluttis, C., Bishaw, T., & Frank, M. W. (2014, December). The workforce for health in a globalized context – global shortages and international migration. *Global Health Action*, *7*(1), 23611. doi: 10.3402/gha.v7.23611

Basso, G., & Peri, G. (2005). The Association between Immigration and Labor Market Outcomes in the United States. , 37.

Bodenheimer, T., Grumbach, K., & Berenson, R. A. (2009, June). A Lifeline for Primary Care. *New England Journal of Medicine*, *360*(26), 2693–2696. doi: 10.1056/NEJMp0902909

Bodenheimer, T., & Pham, H. H. (2010, May). Primary Care: Current Problems And Proposed Solutions. *Health Affairs*, *29*(5), 799–805. doi: 10.1377/hlthaff.2010.0026

Borjas, G. J. (1999). THE ECONOMIC ANALYSIS OF IMMIGRATION. , 64.

Carrier, E. R., Yee, T., & Stark, L. (2011). Matching Supply to Demand: Addressing the U.S. Primary Care Workforce Shortage. (7), 7.

Cooper, R. A., Getzen, T. E., McKee, H. J., & Laud, P. (2002, January). Economic And Demographic Trends Signal An Impending Physician Shortage. *Health Affairs*, *21*(1), 140–154. doi: 10.1377/hlthaff.21.1.140

Docquier, F., & Rapoport, H. (2009). Quantifying the Impact of Highly-Skilled Emigration on Developing Countries. , 115.

Forcier, M. B., Simoens, S., & Giuffrida, A. (2004, July). Impact, regulation and health policy implications of physician migration in OECD countries. *Human Resources for Health*, *2*(1), 12. doi: 10.1186/1478-4491-2-12

Furtado, D., & Ortega, F. (2020). Does Immigration Improve Quality of Care in Nursing Homes? , 42.

Jaeger, D., Ruist, J., & Stuhler, J. (2018, February). *Shift-Share Instruments and the Impact of Immigration* (Tech. Rep. No. w24285). Cambridge, MA: National Bureau of Economic Research. doi: 10.3386/w24285

Kazanjian, A., & Pagliccia, N. (1996, March). Key factors in physicians' choice of practice location: Findings from a survey of practitioners and their spouses. *Health & Place*, *2*(1), 27–34. doi: 10.1016/1353-8292(95)00039-9

Kollar, E., & Buyx, A. (2013). Ethics and policy of medical brain drain: A review. *Swiss Medical Weekly*, *143*, w13845. doi: 10.4414/smw.2013.13845

Lakhan, S. E., & Laird, C. (2009). Addressing the primary care physician shortage in an evolving medical workforce. *International Archives of Medicine*, *2*(1), 14. doi: 10.1186/1755-7682-2-14

Pang, T., Lansang, M. A., & Haines, A. (2002, March). Brain drain and health professionals: A global problem needs global solutions. *BMJ*, *324*(7336), 499–500. doi:

10.1136/bmj.324.7336.499

Petterson, S. M., Liaw, W. R., Phillips, R. L., Rabin, D. L., Meyers, D. S., & Bazemore, A. W. (2012, November). Projecting US Primary Care Physician Workforce Needs: 2010-2025. *The Annals of Family Medicine*, *10*(6), 503–509. doi: 10.1370/afm.1431

Schwartz, M. D. (2012, April). Health Care Reform and the Primary Care Workforce Bottleneck. *Journal of General Internal Medicine*, *27*(4), 469–472. doi: 10.1007/s11606-011-1921-4

Walker, K. O., Moreno, G., & Grumbach, K. (2012). The Association Among Specialty, Race, Ethnicity, and Practice Location Among California Physicians in Diverse Specialties. *Journal of the National Medical Association*, *104*(0), 46–52.

Żuk, P., Żuk, P., & Lisiewicz-Jakubaszko, J. (2019, June). Labour migration of doctors and nurses and the impact on the quality of health care in Eastern European countries: The case of Poland. *The Economic and Labour Relations Review*, *30*(2), 307–320. doi: 10.1177/1035304619847335

8 Appendix

Table 13: Preliminary Regression

	(1) Self-rated health status	(2) BMI	(3) Asthma	(4) Diabetes
FB	-0.0000149	0.000338	-0.0000192	0.0000112
	(0.0000817)	(0.00392)	(0.0000194)	(0.0000351)
Constant	3.789***	28.52***	0.101***	0.0587***
	(0.00791)	(0.748)	(0.00507)	(0.00651)
Observations	88	88	88	88

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Standard errors in parentheses (clustered at the region). Control variables included with yearly and regional fixed effects.

Table 14: First Stage for Foreign-Born IV

	(1) Foreign-Born Instrumental Variable

FB per capita	-0.758**
	(0.362)
Constant	0.0253***
	(0.00259)
F	4.389
N	168

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: First Stage for Growth Local Instrumental Variable

	(1)
	Growth Local Instrumental Variable
Local per capita	12.05***
	(3.021)
Constant	0.331***
	(0.0596)
F	15.90
N	168

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: First Stage for Shift-Share Local Instrumental Variable

	(1)
	Shift-share Local Instrumental Variable
Local per capita	22.51***
	(6.527)
Constant	1.408***
	(0.129)
F	11.90
N	168

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Foreign IV and Shift-Share Local IV with Conditions

	(1) Self-Rated Health status	(2) BMI	(3) Asthma	(4) Diabetes
FB per capita	-38.61	633.6	-7.009	-0.727
	(57.44)	(823.6)	(8.558)	(5.825)
Local per capita	1.933	20.35	-2.135	-0.318
	(11.96)	(140.6)	(1.349)	(1.255)
Constant	5.216***	19.16	0.140	-0.125
	(1.273)	(13.94)	(0.166)	(0.0926)
Observations	132	132	132	132

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Standard errors in parentheses (clustered at the MSA). Control variables included with yearly and MSA-level fixed effects. Conditions are: ratio at 0.05, population at 200)

Table 18: Foreign IV and Shift-Share Local IV with Conditions

	(1) Self-Rated Health status	(2) BMI	(3) Asthma	(4) Diabetes
FB per capita	-29.54	442.8	-4.991	-3.543
	(101.1)	(927.4)	(9.382)	(11.12)
Local per capita	114.8	-1130.3	9.215	14.22
	(214.9)	(2211.5)	(31.38)	(28.05)
Constant	14.30	-83.46	0.926	1.061
	(17.00)	(191.0)	(2.499)	(2.355)
Observations	71	71	71	71

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Standard errors in parentheses (clustered at the MSA). Control variables included with yearly and MSA-level fixed effects. Conditions are: ratio at 0.05, population at 1000)

Table 19: Foreign IV and Shift-Share Local IV with Conditions

labeltab1

	(1)	(2)	(3)	(4)
	Self-Rated Health status	BMI	Asthma	Diabetes
FB per capita	-435.0	215.8	11.29	63.08
	(2571.3)	(4037.7)	(110.1)	(383.3)
Local per capita	-91.57	-166.4	1.754	17.37
	(636.2)	(945.9)	(26.98)	(95.04)
Constant	9.520	14.11	-0.227	-0.675
	(31.71)	(49.02)	(1.286)	(4.702)
Observations	105	105	105	105

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Standard errors in parentheses (clustered at the MSA). Control variables included with yearly and MSA-level fixed effects. Conditions are: ratio at 0.10, population at 200)

Table 20: Foreign IV and Shift-Share Local IV with Conditions

	(1)	(2)	(3)	(4)
	Self-Rated Health status	BMI	Asthma	Diabetes
FB per capita	53.52	243.8	-8.521	-11.33
	(544.0)	(1383.2)	(21.46)	(59.59)
Local per capita	202.0	3.771	-7.549	-21.43
	(897.7)	(2607.5)	(30.54)	(103.1)
Constant	6.142	3.936	-0.0409	-0.0977
	(9.250)	(23.47)	(0.499)	(1.030)
Observations	97	97	97	97

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Standard errors in parentheses (clustered at the MSA). Control variables included with yearly and MSA-level fixed effects. Conditions are: ratio at 0.10, population at 500)

Table 21: Foreign IV and Shift-Share Local IV with Conditions

	(1)	(2)	(3)	(4)
	Self-Rated Health status	BMI	Asthma	Diabetes
FB per capita	155.8	-3355.9	3.026	12.21
	(234.0)	(5558.7)	(15.00)	(17.13)
Local per capita	-47.13	878.1	-1.837	0.785
	(53.79)	(1295.2)	(5.324)	(6.504)
Constant	-8.041	281.2	-0.577	-0.846
	(18.43)	(444.8)	(1.330)	(1.698)
Observations	54	54	54	54

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Standard errors in parentheses (clustered at the MSA). Control variables included with yearly and MSA-level fixed effects. Conditions are: ratio at 0.10, population at 1000)