2018

Does the H-1B Visa Program Impact Quality of Healthcare?

Sarah Yaghmaee
Scripps College

DOES THE H-1B VISA PROGRAM IMPACT QUALITY OF HEALTHCARE?

by

SARAH K. YAGHMAEE

SUBMITTED TO SCRIPPS COLLEGE IN PARTIAL FULFILLMENT OF THE DEGREE OF BACHELOR OF ARTS

PROFESSOR ROBERTO PEDACE
PROFESSOR NAYANA BOSE

DECEMBER 8TH, 2017

Abstract

Recently, the H-1B visa program has been a target of reform under the Trump administration. This study explores whether the employment of H-1B physicians in U.S. hospitals has any effect on the quality of healthcare provided. As indicators of quality, I use patient survey scores as well as mortality and readmission rates. This new econometric evidence suggests that patient perception of quality is not influenced by prejudice toward nonimmigrant physicians, but provides inconclusive results for the rate-based measures of healthcare quality.

Acknowledgments

I would like to thank Professor Pedace and Professor Bose for their patient guidance and feedback throughout the process of drafting and completing my thesis. Under their instruction, I became comfortable working with data and statistical programs as well as conducting econometric analysis. This project would not have been possible without them.

I would also like to thank my family for their unwavering support and for providing me with the opportunity to attend Scripps. I greatly appreciate how much my success means to them. I am very grateful to my dad for helping me find a topic that I was excited to research and for taking the time to comment on my drafts, even in the middle of the night. To my mom, thank you for all your encouragement, especially during the most stressful periods. Finally, I want to thank my sister for always believing in me, reminding me to stay on track when I get distracted, and sending me pictures of our dogs to help me get through all the work.

Table of Contents

I. Introduction

For many years, immigration policy has been a heavily controversial subject in economic and political fields. The debate has been further intensified by the most recent presidential campaigns and the subsequent election. Even at the most superficial level of analysis, there is a definite relationship between immigration and the economy. Immigration expands two economic parameters; the supply of workers in labor markets and the total consumption of goods both increase with the number of migrants. Though these results can be interpreted as beneficial for the economy, the debate lies mostly in the increased competition for American citizens to gain employment. Roughly 13 percent of the U.S. population consists of immigrants, yet they make up 16 percent of the labor force and own more small business than U.S.-born workers because they are disproportionately concentrated at the peak working age range[1]. In the political dimension, many legislators and citizens alike argue that immigration laws should become more stringent to protect American jobs.

One of the latest targets for immigration policy reform is the H-1B visa program. The H-1B program was created in 1990 to grant visas to skilled nonimmigrant workers. Under the program, skilled workers are defined as having at minimum a bachelor's degree or the equivalent. Currently, the cap on foreign workers is 65,000 per year, with an additional 20,000 granted to those who received a master's or doctorate degree in the U.S. The lottery by which the visas are granted has two stages. First, there is a lottery for the 20,000 with advanced degrees. The secondary step is for the bachelor's degree category. Those who were not selected in the first round are entered

[1] Economic Policy Institute, "Facts About Immigration and the U.S. Economy"

into the drawing for 65,000 slots. If the cap is reached in the first 5 business days, there is an additional preliminary lottery to decide which applications are processed. H-1B visas are in such high demand that in every year since 2013, the cap has been reached within this designated time period[2]. The visas are especially sought after by foreign workers in STEM fields, such as engineering, computer science, architecture, and medicine[3]. H-1B visas are effective for a period of three years, which can be extended to six years through a second application.

Employers sponsoring H-1B petitions face certain economic stipulations put forth by the Department of Labor to ensure they comply with the intention of the visa program[4]. They must compensate foreign workers with either the set wage for the position within the company or the prevailing wage in the industry set by state employment agencies, whichever is higher. Sponsors are required to declare that the hiring of H-1B workers will not have a negative impact on the working conditions of other employees in the company. If for any reason work is halted (e.g. strikes), the employer must notify the Department of Labor within 10 days. The final blanket requirement for H-1B sponsors is creating a public access file for inspection with proof of meeting all the stipulations. If greater than a certain percentage of employees are H-1B workers, employers are obliged to declare that the foreign workers are not displacing domestic workers as well as provide proof of attempts to recruit American workers.

[2] American Immigration Council, "The H-1B Visa Program: A Primer on the Program and Its Impact on Jobs, Wages, and the Economy"
[3] Statista, "Which U.S. Industries File Most Work Visa Applications?"
[4] H1 Base, "Information for H1B Employers"

Citing the intent to keep jobs for domestic workers, in April 2017 the Trump administration temporarily halted expedited processing for H-1B visas, under which applications are reviewed within 15 days. Expedited processing was resumed on August 18th for first-time applicants, and on October 3rd for extended-stay petitions[5]. The need for expedited processing becomes evident when taking into account that regular processing for applications can take over six months.

For the healthcare industry, the removal of expedited processing may have potentially adverse consequences. Over 1,500 non-citizens who were offered residency positions at U.S. hospitals were put at risk of not receiving their visa in time by the suspension of expedited processing[6]. Hospitals that hired foreign physicians for their residency programs under the expectation that the visas would be quickly granted suffered from issues related to insufficient staffing, which may include a reduction in comprehensive individual care for patients, longer wait times for appointments, and time spent searching for replacements. These costs could compromise the quality of care that hospitals are able to provide for their patients. The staffing issues are especially pronounced in rural areas, which already suffer from doctor shortages and partially depend on the H-1B program to fulfill the healthcare needs of their populations[7]. Because American doctors are typically disinclined to serve in these areas, H-1B visa-holders constitute a high percentage of practicing physicians in rural towns.

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[5] U.S. Citizen and Immigration Services, "H-1B Fiscal Year (FY) 2018 Cap Season"
[6] Parija Kavilanz, "Hospitals, doctors in limbo after fast-track processing of H-1Bs is halted"
[7] Michael Ollove, "Foreign-born doctors, many in underserved areas, are worried about their jobs"

The defined question that this paper will explore is whether the hiring of physicians with H-1B visas has an impact on the quality of healthcare that hospitals provide. To answer this question, I will provide new econometric evidence. In the following sections, I will analyze the existing literature from various branches of economics, present my data, model, and results, and demonstrate my findings through the research I have conducted.

II. Literature Review

While the impact of the H-1B visa program has been studied extensively in the information technology industry, and there is a plethora of research on the quality of medical care, literature regarding the effect of physicians with H-1B visas on the quality of healthcare is scarce, if at all available. The lack of research is important to address. Healthcare is one of the industries most affected by the H-1B program, behind technology, with 8,100 applications submitted by medical professionals in 2016[8]. Additionally, healthcare is one of the largest industries in the U.S. If the quality of services is in any way affected by the presence of skilled nonimmigrant workers, the ability to measure that effect would be momentous. To overcome the research shortage, we must synthesize two separate branches of economic research: labor markets and healthcare. Because immigration is as much a political issue as an economic one, it is also essential to consider existing research on policy.

[8] Statista, "Which U.S. Industries File Most Work Visa Applications"

A. The Impact of H-1B Visas on Labor Markets

As mentioned before, studies regarding the impact of the H-1B program on labor markets generally specific to the IT sector, being the predominant industry with H-1B visa applicants. Two studies I reviewed had consistent results. The Bound et al. 2017 study compares the effects of the H-1B program on the IT sector in relatively open and closed economies. In the sample, they analyze the recruitment of H-1B computer scientists in the IT sector during the Internet boom from 1994 to 2001. They create two predominant models: 1) a product market in which IT firms produce goods to sell to consumers, and 2) a labor market for college graduates (i.e. skilled workers). The models include maximization functions for firm profits and utility functions for consumption. After statistical analysis, they conclude that in an open economy, the visa program raises profits in the IT sector and contributes to innovation within the firms in which it is implemented (Bound et al. 2017). More broadly, it can lower prices of goods and increase consumption.

A noteworthy concern raised is that nonimmigrant workers might displace domestic workers. The study states that critics of the program claim employers recruit cheap foreign labor to replace domestic workers. The empirical evidence discovered through their research appears to support this conclusion. Bound et al. 2017 finds that the H-1B visa program crowds out domestic workers: the hiring of H-1B computer scientists seems to cause domestic computer scientists to move into non-CS fields, which lowers the average wages in the firms. When interpreting the results, Bound et al. 2017 suggests that the positive effects of the H-1B program may not fully offset the negative ones.

An earlier study by Doran et al. 2014 has similar conclusions: the H-1B visa program appears to result in lower average earnings and higher firm profits in the IT sector. Doran et al. 2014 also finds evidence for the presence of a crowding out effect. They argue that the crowding out effect is substantial enough that H-1B and non H-1B workers might be perfect substitutes (Doran et al. 2014). This conclusion may be extreme, especially when considering the cost to firms for sponsoring visa applications as well as employer willingness to hire temporary workers with the knowledge that they must be replaced in the foreseeable future.

By contrast, a third study contests the definitive conclusion of the crowding out effect in H-1B sponsoring firms. Luthra 2009 argues there is existing empirical evidence for both the presence and absence of the crowding-out effect, and as such, the debate is more political than empirical. In a similar vein to Bound et al. 2017 and Doran et al. 2014, Luthra claims that the H-1B program increases the flexibility of labor and production in firms (Luthra 2009).

However, the Luthra 2009 study has a different focus. She analyzes whether the likelihood of contingent employment varies between immigrants who have lived in the U.S. for a time period shorter than six years (a group she uses as representative of H-1B workers) and longer-term residents. The primary finding is that immigrants who have been in the U.S. for fewer than six years are more likely to be contingent workers, and empirical evidence supports that contingent workers receive fewer benefits than long-term employees. A secondary conclusion is that contingent workers do not receive lower wages than permanent workers. Luthra 2009 also argues that H-1B visas are in high demand despite their short-term disadvantages, such as fewer employment options and benefits, because the foreign workers who apply plan to eventually become U.S. citizens. It would be interesting in future research to explore whether former H-1B workers who become permanent residents create a long-term crowding out effect.

B. Measures of Healthcare Quality

Over time, measures of the quality of healthcare have been standardized by researchers and healthcare professionals. Mainz 2003 defines and describes various indicators of quality in his paper. He states that typically, these indicators are established through existing evidence and literature or agreed upon by a panel of health experts. The first category Mainz 2003 mentions is rate-based indicators, such as the percentage of patients who are infected during surgery and the number of patients who die in surgery. A second broad category is structure and process indicators, which includes the proportion of specialists to other doctors, the number of beds in the hospital, and the use of diagnostic technologies. Mainz 2003 claims that for the indicators in this category to be reliable, they must be correlated with a desirable effect on health outcomes. The aforementioned rate-based indicators, as well as patient satisfaction, are examples of outcome indicators, and their usage is ideal for analyzing long-term data (Mainz 2003).

In econometric studies, we see that the types of indicators Mainz 2003 details are frequently used to evaluate quality of healthcare. Clark 2006 uses an outcome indicator, creating a quantitative survey given to patients, physicians, and other hospital employees to evaluate the quality of healthcare provided. He perceives these three groups as “the three co-creators of health” (Clark 2006). His findings suggest that good organization and strong relationships between patients, physicians, and employees lead to patient base retention and growth, which is reflective of the quality of care. He claims such relationships determine a hospital's success (Clark 2006).

Lichtenberg 2011 instead utilizes process and structure indicators to measure the effect of healthcare quality on average life expectancy. He considers the percentage of advanced diagnostic imaging procedures used, the percentage of physicians at a hospital who attended top-ranking medical schools, and the average quality of prescription drugs. Lichtenberg 2011 finds as the primary result that each of the three indicators is statistically significant, and each increases the average life expectancy. Additionally, Lichtenberg 2011 concludes that an increase in life expectancy is not correlated to health insurance rates or education levels of patients, and that states increasing their spending on diagnostic imaging do not have higher per capita medical expenditures.

C. Politics of Nonimmigrant Work

One researcher poses the question of whether the growth rates of various nonimmigrant worker groups affect the likelihood of elected state officials passing E-Verify policies (Udani 2016). Under these policies, employers are entitled to review the work authorization of new employees to ensure they are legally working in the U.S. As test groups, Udani 2016 focuses on H-1B workers (high-skilled) as well as H-2A and H-2B workers (non-specialty, employed in agricultural and non-agricultural fields, respectively). As explanatory variables, he considers annual state unemployment rate, the percentage of Democratic officials in state legislatures, states using E-Verify as pilot program, and whether neighboring states have enacted E-Verify policy within the previous year. In a second regression, Udani 2016 incorporates proxies for racial prejudices; he uses the immigration rates from Asian countries to represent the model minority stereotype, and the Mexican immigration rate as representative of the low-skilled labor stereotype.

In both models, the results are statistically significant. Udani 2016 finds that states with high growth rates of H-1B workers adopt E-Verify policies more slowly, while states with high growth rates of non-specialty immigrant workers pass these policies more quickly. He argues that the high demand for H-1B workers supports stereotypes of 'good' workers, and takes away the motivation to create legislation for employee verification. Udani 2016 concludes state officials have ambiguous attitudes toward immigration, and legislation is largely dependent on American perceptions of immigrant groups, in which both class bias and racial bias have central roles.

III. Data

In creating my dataset for this empirical analysis, I collected data from four different sources. The first source I encountered was the My Visa Jobs website, which provided data on the number of certified, certified-withdrawn, denied, and withdrawn applications sponsored from 2013 to 2016 by the top 100 sponsoring hospitals and networks in the U.S. In my analysis, I decided to include only the number of certified physicians. Initially, I had hoped to include data from these four years, but the Census Bureau, another source I consulted, did not release demographic information for 2016 early enough for the purposes of this project. Thus, my dataset was constrained to 2015 on the upper side. For area characteristics, I noted whether each hospital was located in an urban or rural area using U.S. News Health. Finally, I referred to archived Physician Compare and Hospital Compare datasets made available by Medicare. The former provided the total number of physicians per hospital and per network, and the latter supplied data for my chosen dependent variables. The data is cross-sectional and strongly balanced, organized by the generated hospital identification variable and year. Descriptive statistics for each variable are listed in Table 1 in the Appendix. The calculated sample means and standard deviations for the variables are reasonable, which suggests a lack of major mistakes in collecting data.

As stated before, the number of H-1B certified physicians for the top 100 sponsoring hospitals and networks came from the My Visa Jobs website. Because my goal was to measure the effect of the visa program on individual hospitals, an immediate issue was to maximize the amount of available data used in my regressions. As a solution, I gathered data on both dependent and explanatory variables for the individual hospitals associated with each network. I created one dataset for individual hospitals, and another for H-1B data for networks. Then, I created a network identification variable to match individual hospitals to their respective networks. Additionally, because there were multiple observations for each year, I created a hospital identification variable. There were issues with repeat observations; some of the hospitals for which individual data was reported were also included in networks, and some were members of multiple networks. Another limitation was missing observations for certain hospitals. After dropping those data points, the dataset included a total of 293 observations.

For specific information about hospitals, I used archived Medicare datasets. Medicare reported data on the number of physicians per hospital and per network in its Physician Compare datasets, which was useful given the similar reporting of H-1B certification. From this data, I calculated the percentage of physicians with H-1B visas employed by individual hospitals and networks for every year. In the case of networks, the same percentage was applied to each constituent hospital. However, Medicare did not provide physician data prior to 2014. Under the assumption that the number of physicians employed per hospital would not drastically vary between years, I repeated the value given in 2014 for 2013. A second limitation was the unavailability of physician data for certain hospitals in my dataset. For these hospitals, I used the value listed on each hospital website as a repeat observation for each year. The Hospital Compare datasets from 2013 to 2015 provided data on all the dependent variables: HCAHPS base score, HCAHPS consistency score, the 30-day heart failure mortality rate, the 30-day heart failure readmission rate, and the 30-day hospital-wide readmission rate. The datasets also included whether each hospital was owned by the government, a for-profit company, or a nonprofit; I included ownership as a potential explanatory variable for quality of healthcare.

I utilized the Fact Finder tool to find information about the median inflation-adjusted wage, median population age, and number of males per 100 females for the cities in which the hospitals were located. With a higher median wage, the population in question likely has a greater amount of disposable income, presumably leading to more effective demand for a better quality of healthcare. Living in a city or town with higher average wages may also be a source of attraction for physicians who seek to pay off their student loans. Median age may have a potentially large impact on the demand for healthcare as well. Similarly, urban areas may be more appealing to physicians than rural towns. It has been well-documented that medical needs increase with age. I chose to include the number of males per 100 females in my regressions because men and women have different healthcare needs, which may also affect the quality of services provided by hospitals.

IV. Model

My model analyzes the effect of H-1B employment on the quality of healthcare based on the five different dependent variables previously mentioned: HCAHPS base score, HCAHPS consistency score, the 30-day heart failure mortality rate, the 30-day heart failure readmission rate, and the 30-day hospital-wide readmission rate. I ran linear multiple regressions with each dependent variable to examine the potential impact of the program.

HCAHPS is a hospital scoring system based on patient evaluations regarding eight different categories, including effectiveness of nurse and doctor communication, pain management, and cleanliness[9]. Patients only fill out one HCAHPS survey, but two separate scores are calculated. The base score is calculated out of 80 points, rewarding hospitals for achievement and improvement in each of the eight categories. By contrast, the consistency score is scored out of 20 points and reports hospitals' lowest-performing

[9] Centers for Medicare and Medicaid Services, "CMS Issues Final Rule for First Year of Hospital Value-Based Purchasing Program"

category[10]. Because Medicare reported the scores independently, I decided to run separate regressions rather than combining the scores into one variable. Although patient surveys are not subjective indicators of quality of care, perception may have a discernible effect on health outcomes. For example, patients who feel that they are receiving high-quality care might experience a placebo-like effect that could contribute to their healing process.

The remaining three dependent variables – heart failure mortality rate, heart failure readmission rate, and hospital-wide readmission rate – I chose due to their status as standard indicators for quality of healthcare. Accessibility also shaped my decision; many of the reported variables in the Medicare datasets were not supplemented by a code to explain the scoring system. The values for mortality and readmission were widely available, and as each observation was a percentage, interpretation was straightforward.

All five regressions were in the same format, with only the dependent variable changing between regressions:

$$Y_i = h1b * X_{i1} + areachar * D_{i1} + medianinc * X_{i2} + hospown1 * D_{i2} + hospown3 * D_{i4} + medage * X_{i3} + mfratio * X_{i4} + u_i$$

symbolically written as:

$$Y_i = \beta_1 X_{i1} + \beta_2 D_{i1} + \beta_3 X_{i2} + \beta_4 D_{i2} + \beta_5 D_{i4} + \beta_6 X_{i3} + \beta_7 X_{i4} + u_i$$

[10] HCAHPS Fact Sheet, November 2017

Here, *h1b* is defined as the percentage of physicians with H-1B visas at each hospital. *Areachar* is a binary variable set equal to 0 if the hospital is in an urban area and 1 if the hospital is rural. *Medianinc* is the median inflation-adjusted wage for the population in the city or town where the hospital is located. *Hospown1* is equal to 0 if the hospital is government-owned, and *hospown3* is equal to 0 if the hospital is nonprofit. *Medage* is the average age of the population and *mfratio* is the number of males per 100 females; both are specific to the hospital's location.

My null hypothesis for the model was statistical insignificance of the coefficients of all the explanatory variables ($\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0$). To correct for heteroskedasticity, I conducted random-effects GLS regressions. I chose random-effects over fixed-effects because the coefficients of my explanatory variables did not change between the corrected and uncorrected regressions. I deemed it unnecessary to correct for multicollinearity due to low R^2 values in each regression, which will be addressed in the results. Additionally, I decided not to correct for autocorrelation, as my data was not time series.

V. Results[11]

A. Regression 1: HCAHPS Base Score

In the first regression, the only variables found to be statistically significant were median inflation-adjusted wage ($\beta_3 = 0.00022,\ p > |z| = 0.000$) and nonprofit hospital ownership ($\beta_5 = -9.344,\ p > |z| = 0.015$). The magnitude of median wage

[11] The full results of my statistical analyses are detailed in the index

at first appears small enough to be negligible: with an increase of $1, the base score increases by 0.00022 point. It is more compelling, however, to consider substantial changes in median wage. With a $10,000 increase, for example, the base score is expected to increase by 2.2 points. This may imply that the cost of living is so high that income must considerably increase to make a substantial difference in the perceived quality of healthcare.

Nonprofit hospital ownership has a more immediately obvious effect on the base score. If the hospital is run by a nonprofit organization, the base score is expected to be lower by 9.344 points than otherwise. Area characteristics are nearly statistically significant ($\beta_2 = 5.30,\ p > |z| = 0.079$). Perhaps with a larger sample size, I would have found statistical significance. The model explains approximately 15.04 percent of the variation in the HCAHPS Base Score.

B. Regression 2: HCAHPS Consistency Score

In the second regression, the median inflation-adjusted wage remains statistically significant, with a coefficient of 0.0000439 and a p-value of 0.005. With a $10,000 increase in median income, the consistency score is predicted to increase by 0.439 point. To compare the magnitude to that of the HCAHPS base score, I scaled the base score down to 20 and found a predicted increase is 0.55 point for a $10,000 increase in median inflation-adjusted wage. When on the same scale, the coefficients are similar, with roughly a 20 percent difference. This should not be surprising, given the shared origin of the two scores. Again, it implies that a large change in income is required for a discernible difference in patients' perception of the quality of healthcare provided.

Area characteristics are also statistically significant in this regression: if the hospital is in a rural area, the consistency score is expected to increase by 1.67 points ($p > |z| = 0.016$). This model explains roughly 16.16 percent of the variation in the HCAHPS Consistency Score.

C. Regression 3: 30-Day Heart Failure Mortality Rate

In the 30-day heart failure mortality rate regression, the median inflation-adjusted wage is no longer statistically significant. Area characteristics are again found to be significant. The mortality rate is predicted to be 1.24 percent higher in rural areas in comparison to urban areas ($p > |z| = 0.000$). One potential explanation for this result is that hospitals may be farther or more difficult to access in rural areas, and patients might not arrive in time for effective treatment.

Government hospital ownership is another statistically significant explanatory variable, predicted to decrease the mortality rate by approximately 0.89 percent ($p > |z| = 0.015$). One possibility is that government-run hospitals have stricter guidelines for healthcare providers, leading to a lower mortality rate.

Of the five regressions, this is the only one to result in the statistical significance of the percentage of H-1B physicians ($p > |z| = 0.003$). For every 5 percent increase in visa-holding physicians, the mortality rate is expected to increase by 0.245 percent. This effect is miniscule and arguably economically insignificant. The model explains approximately 13.8 percent of the variation in the 30-day heart failure mortality rate.

D. Regression 4: 30-Day Heart Failure Readmission Rate

When running a statistical analysis on the 30-day heart failure readmission rate, the only statistically significant explanatory variable is area characteristics ($\beta_2 = -1.10,\ \ p > |z| = 0.001$). The implication is that the heart failure readmission rate in rural hospitals is 1.10 percent lower than in urban hospitals. It may be that rural hospitals with fewer specialized physicians send patients to major hospitals in urban areas, thus explaining the lower readmission rate.

In this regression, the male to female ratio is statistically significant at the 10 percent level, but not at the 5 percent level ($\beta_7 = -0.49, p > |z| = 0.071$). This result might change with a larger sample size. The model explains roughly 12.52 percent of the variation in the 30-day heart failure readmission rate.

E. Regression 5: 30-Day Hospital-Wide Readmission Rate

In the final regression, three explanatory variables are statistically significant: area characteristics, median inflation-adjusted wage, and government ownership. If the hospital is rural, the hospital-wide readmission rate is expected to decrease by 1.06 percent ($p > |z| = 0.000$) as compared to urban hospitals. As stated before, this may result from sending patients to major urban hospitals.

Median income has such a small effect on the readmission rate that it may be negligible altogether. If income increases by $10,000, the hospital-wide readmission rate decreases by roughly 0.08 percent ($p > |z| = 0.028$).

Lastly, if a hospital is government-owned, the readmission rate is predicted to decrease by about 1.06 percent ($p > |z| = 0.026$). A possible explanation is the fact that government-owned hospitals are penalized for high readmission rates. As a consequence, they may admit less severe cases to keep their readmission rates low. The model explains approximately 29.95 percent of the variation in the 30-day hospital-wide readmission rate. In this regression again, the male to female readmission rate is only significant at the 10 percent level ($\beta_7 = -0.027, p > |z| = 0.073$).

VI. Discussion

Because the statistical significance of my explanatory variables is inconsistent across the five regressions, the results of my empirical analysis are inconclusive. Therefore, I cannot make any definitive claims regarding the effects of my explanatory variables on the quality of healthcare. In one instance, the coefficients for an explanatory variable (area characteristics) have opposite signs in regressions with different quality indicators, indicating that overall hospital quality is much more difficult to measure than I had previously anticipated.

The statistical insignificance of the percentage of H-1B physicians in the regressions with patient survey results has compelling implications. It suggests that the presence of H-1B certified physicians does not impact patient perception of care. More importantly, this implies an absence of prejudice toward foreign workers in evaluating the quality of care. Even if the results had been significant, the predicted change would have been increased HCAHPS base and consistency scores, which is a fascinating result. It does not appear to contradict existing literature. The finding that highly educated nonimmigrant physicians are not perceived as providing an inferior quality of healthcare reflects the possibility of class bias rather than racial bias, which complements the Udani 2016 results.

I was surprised that median population age was not significant in any of the five regressions. It may be attributed to the limited range of median age in my sample; the lower bound is 23.1 years and the upper bound is 53.1 years. Had I used a measure to encompass the elderly population, I may have found that age has a significant impact on the quality indicators of healthcare included.

There are a couple of limitations in my model that must be addressed in future research. First, because my sample comes from the top 100 sponsoring hospitals and networks rather than a random selection, there is potential for selection bias. I cannot conclude for certain whether sponsorship is correlated with other factors related to quality. Secondly, the potential exists for endogeneity. For example, an indicator of quality might affect the number of applicants a hospital sponsors instead of the reverse, which I specified in my model.

I was slightly disappointed by the low R^2 values obtained from each regression, but unsurprised by this result because there were additional explanatory variables I wanted to include for which I could not find data. In future analysis, variables that I would like to analyze are health insurance rates, the quality of education for both physicians and the general population, whether the physicians were educated abroad or in U.S., and the average physician salary. I would also like to expand my sample size in subsequent work to observe whether statistical significance and the magnitudes of the coefficients of my variables change.

A point of future research might be to explore whether the H-1B visa program has common labor market outcomes between the healthcare industry and the IT industry. It would be interesting to discover whether physicians working in hospitals that sponsor H-1B applications are subject to lower average wages and if there is a crowding-out effect for domestic physicians. Given the shortage of doctors in rural towns, I suspect that the crowding-out effect would be absent. The findings of such a study could have major implications for immigration policy. Perhaps the cap on H-1B visas might be revised, or a certain number of visas would be specifically designated for medical professionals.

VII. Appendix

A. Variable Definitions

h1b	percentage of phyicians per hospital that are H-1B visa holders
areachar	=0 if hospital in urban area, =1 if rural
medianinc	median income in the area in which a hospital is located
hospown1	=0 if hospital is government-owned
hospown2	=0 if hospital ownership is proprietary (omitted)
hospown3	=0 if hospital is nonprofit
mfratio	number of males per 100 females in area where hospital is located
HCAHPSbase	base patient satisfaction score (out of 80)
HCAHPScons	hospital consistency score as rated by patients (out of 20)
hfmr	30-day heart failure readmission rate
hfrr	30-day heart failure readmission rate
orr	30-day hospital-wide readmission rate

B. Tables

Table 1: Summary Statistics

Variable	*Observations*	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
h1b	293	6.710634	5.95099	0	29.701
areachar	293	0.2264505	0.4480074	0	1
medianinc	293	47977.05	19621.76	25697	143017
hospown1	293	0.7610922	0.4271459	0	1
hospown3	293	0.2764505	0.4480074	0	1
medage	293	35.54812	5.397764	23.1	53.1
mfratio	293	92.88157	5.439808	70.6	116.2
HCAHPSbase	293	19.83959	13.7718	0	73
HCAHPScons	293	15.30034	3.895717	3	20
hfmr	293	11.39966	1.925451	7.7	17.8
hfrr	293	22.31365	2.302787	15.9	28.6
orr	293	16.2785	1.262437	13.3	20.1

Table 2: Coefficients and Standard Errors

Explanatory Variable	*Reg 1: HCAHPS Base Score*	*Reg 2: HCAHPS Consistency Score*	*Reg 3: HF Mortality Rate*	*Reg 4: HF Readmission Rate*	*Reg 5: Overall Readmission Rate*
H-1B	.1215774	.0517644	.049244	-.0359008	.0149417
	(.1684432)	(.0461279)	(.0157509)	(.0230185)	(.0148334)
Area Characteristics	5.295546	1.67405	1.248165	-1.102766	-1.058881
	(3.015862)	(0.6951887)	(.2931554)	(.3258784)	(.2104384)
Median Income	.0002201	.0000439	.0000101	-5.10e-06	-8.29e-06
	(.0000498)	(.0000151)	(.0000102)	(7.16e-06)	(3.77e-06)
Government-Owned	-4.535456	-1.0859	-.8866656	-.6131255	-.9011608
	(4.498514)	(1.923974)	(.3632007)	(.6622426)	(.4057055)
Nonprofit	-9.344216	-2.922484	-.5251336	.6315021	.1124094
	(3.827671)	(1.676985)	(.3488361)	(.6154594)	(.3729151)
Median Age	-.1384387	-.0687482	-.001131	.0284989	-.0101258
	(.3559948)	(.0687482)	(.0231396)	(.0316466)	(.0207126)
MF Ratio	-.0174617	-.0048168	.0166812	-.0485827	-.027623
	(.1890167)	(.0371325)	(.0190811)	(.0268757)	(.0153875)
Constant	20.80459	15.32706	9.509636	26.89952	20.43958
	(23.94355)	4.950003	(2.198073)	(2.954671)	(1.701021)

Table 3: Probabilities

Explanatory Variable	*Reg 1: HCAHPS Base Score*	*Reg 2: HCAHPS Consistency Score*	*Reg 3: HF Mortality Rate*	*Reg 4: HF Readmission Rate*	*Reg 5: Overall Readmission Rate*
H-1B	z=0.72	z=1.12	z=3.13	z=-1.56	z=1.01
	P|z|=0.470	P|z|=0.262	P|z|=0.002	P|z|=0.119	P|z|=0.314
Area Characteristics	z=1.76	z=2.41	z=4.26	z=-3.38	z=-5.03
	P|z|=0.079	P|z|=0.016	P|z|=0.000	P|z|=0.001	P|z|=0.000
Median Income	z=4.42	z=2.90	z=0.99	z=-0.71	z=-2.20
	P|z|=0.000	P|z|=0.004	P|z|=0.322	P|z|=0.476	P|z|=0.028
Government-Owned	z=-1.01	z=-0.56	z=-2.44	z=-0.93	z=-2.22
	P|z|=0.313	P|z|=0.572	P|z|=0.015	P|z|=0.355	P|z|=0.026
Nonprofit	z=-2.44	z=-1.74	z=-1.51	z=1.03	z=0.30
	P|z|=0.015	P|z|=0.081	P|z|=0.132	P|z|=0.305	P|z|=0.763
Median Age	z=-0.39	z=-0.70	z=-0.00	z=0.90	z=-0.49
	P|z|=0.697	P|z|=0.487	P|z|=0.996	P|z|=0.368	P|z|=0.625
MF Ratio	z=-0.09	z=0.13	z=0.87	z=-1.81	z=-1.80
	P|z|=0.926	P|z|=0.897	P|z|=0.382	P|z|=0.071	P|z|=0.073
Constant	z=0.87	z=3.10	z=4.33	z=9.10	z=12.02
	P|z|=0.385	P|z|=0.002	P|z|=0.000	P|z|=0.000	P|z|=0.000

Table 4: 95% Confidence Intervals

Explanatory Variable	*Reg 1: HCAHPS Base Score*	*Reg 2: HCAHPS Consistency Score*	*Reg 3: HF Mortality Rate*	*Reg 4: HF Readmission Rate*	*Reg 5: Overall Readmission Rate*
H-1B	-.2085651	-.0386446	.0183728	-.0810162	-.0141312
	.45172	0.1421734	.0801153	-.0092146	.0440146
Area Characteristics	-.6154351	0.3115055	.6735912	-1.741476	-1.471333
	11.20653	3.036595	1.822739	-.4640564	-.6464299
Median Income	0.0001225	0.0000142	-9.88e-06	-.0000191	-.0000157
	0.0003177	0.0000736	.0000301	8.94e-06	-8.99e-06
Government-Owned	-13.35238	-4.856819	-1.598526	-1.911097	-1.696329
	4.281469	2.685019	-.1748054	.6848462	-.1059926
Nonprofit	-16.84631	-.6209313	-1.20884	-.5747761	-.6184907
	-1.842119	.3643455	.1585726	1.83778	.8433096
Median Age	-.8361757	-.1825774	-.0454659	-.0335274	-.0507218
	.5592984	.0869106	.0452397	.0905252	.0304701
MF Ratio	-.3879276	-.0679615	-.0207171	-.101258	-.0577819
	0.3530043	.0775951	.0540794	.0040926	.002536
Constant	-27.52534	5.625232	5.201492	21.10847	17.10564
	67.21794	25.02889	13.81778	32.69057	23.77352

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