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# Impact of Demand for H1B Visas in the US on the Performance of Listed Indian Firms

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# Impact of Demand for H1B Visas in the US on the Performance of Listed Indian Firms

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**Abstract**

This thesis examines the relationship between Indian firm performance and the demand for H1B visas in the US. To test this relationship, a fixed effects model has been used on a panel dataset of 104 Indian firms listed on the Bombay Stock Exchange (BSE) and National Stock Exchange of India (NSE) over the period 2009 to 2021. The results show that an increase in H1B visa demand is negatively and significantly associated with Indian firm performance. These findings suggest that the US's demand for high skilled labor overseas has consequences for firms in the home country.

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# 1 Introduction

The impact of policies on firm performance is commonly studied in economics. Among these policies, those relating to immigration, when one comes to another country, have received recent academic attention. See, for instance, Kerr et al. (2015). Immigration studies focus on the country that people are coming to. For example, there are extensive studies on the impact of skilled immigration to the US on US firms. Emigration, when one leaves their country, on the other hand, has not received as much attention. Continuing the same example, research is lacking on the impact of skilled immigration to the US on Indian firms. All immigrants are emigrants, and the gap between immigration and emigration studies must be filled. This thesis aims to contribute to emigration studies by examining the impact of H1B visa demand in the US on the performance of Indian companies.

H1B visas are skilled immigrant worker visas issued in the US. According to the USCIS (United States Citizenship and Immigration Services), to apply for an H1B visa, an applicant must meet three requirements: an offer of employment from a US firm for a role that requires specialty knowledge, proof of a bachelor's degree in the field, and evidence from the employer that there is a lack of qualified US applicants for that role. First, the applicant must submit their documentation to the USCIS and wait for approval. If they get approved, the employer must file a petition on the applicant's behalf. If the petition is accepted, the applicant's visa is sent into a lottery process. The lottery awards applicants with visas randomly, and the number of visas awarded have a cap. As of 2022, the cap is at 65,000 visas with an extra 20,000 for applicants with a master's degree. Applicants that are awarded the visa can begin work once the visa is valid. Moreover, applicants who are denied because of the cap can apply in the following year and be part of the lottery process once again.

The strict and demanding requirements of H1B visas confirm that the workers that receive the visas are in fact skilled. The demand for H1B visas is, hence, used as a proxy for the amount of skilled labor leaving India. There is an incredibly high demand for H1B visas. The data shows that the number of applicants in the lottery has risen from 227,477 in 2009 to 475,123 in 2021. Currently, 74% of visa holders in the US are Indians, which sheds light on how most of this demand is coming from India (Kably, 2022). This large and increasing demand is the result of a large wage gap between US and Indian workers. For the same work, US workers are paid far more than Indian workers. Thinking financially, employees that realize this would have a strong preference to switch jobs. In essence, the high-skilled worker supply in India is threatened by the H1B visa program that gives these workers an opportunity to pursue the same career with a much higher compensation.

The goal of this thesis is to understand how the loss in high skilled workers affects Indian firms. A balanced panel dataset of 104 Indian firms observed annually from 2009 to 2021 has been used to answer this question. Each Indian firm is grouped into 18 industries based on the North American Industry Classification System (NAICS). Indian firm performance, the dependent variable, is measured by the return on assets (ROA) in each year. The independent variable of interest is the number of H1B visa petition approvals, a proxy for H1B visa demand, in each of these industries. A large H1B visa demand in an industry is used as an indication of a large potential loss of high skilled workers in that industry in India. To estimate the impact of this H1B visa demand on ROA, a fixed effects model has been used that controls for both time invariant firm fixed effects and firm invariant time fixed effects.

The results of the fixed effects regression show a negative and significant relationship between H1B visa demand and Indian firm performance. Thus, the hypothesis that Indian firm performance is negatively impacted by the loss of high-skilled labor to the US is confirmed. These results help Indian firms recognize that they must make efforts to shorten the wage gap. Indian firms should also consider creative human resources strategies to make local jobs more appealing than those in the US. Moreover, the results could encourage the Indian government to uplift the skills of the local population. This would reduce the drawbacks of losing high skilled workers to more appealing jobs in the US.

## 2 Literature Review

Over the last four decades, literature has developed an important toolkit to study the economic consequences of immigration. As with any economic phenomenon, there are many lenses through which one can explore these consequences. However, researchers only began studying skilled immigration in the last two decades. According to Lincoln (2015), their work has reflected an adoption of existing methodologies that were developed too study immigration in a general sense. As a result, there has been disagreement in choosing the right tools to study skilled immigration.

In the US, the skilled immigration program allows firms to choose the workers that they want to hire. Hence, US firms play an active and essential role in skilled immigration, but this has not been researched enough. Given the policies of the immigration program, Lincoln (2015) asserts that literature studying consequences of skilled immigration from the lens of US firms in greater depth will be more valuable than the toolkit used for broader migration studies.

In 2021, 74% of H1B visas were given to Indians (Kably, 2022). Lincoln (2015) provides evidence that links hiring skilled immigrants to greater employment of skilled workers by US firms, a greater share of the firm's workforce being skilled, and a higher share of skilled workers being immigrants. US firms mostly hire skilled immigrants only if they cannot find a comparable worker from the US. Not only do these results imply the larger point that it is important to consider the US firms in researching immigration, but also the fact that talent is being drawn from India to the US.

On average, software workers in the US earn about 71,000 US dollars per year more than in India (Clemens, 2013). There are three possible reasons for the large difference in wages: US and Indian workers might be doing the same work but earn different wages because they produce imperfectly tradable goods, the US worker might do more or better work because they have better technology or capital, or the US worker might do more or better work because of their location alone. Clemens' (2013) results suggest that the gap in wages arises mainly from location. Most of the difference cannot be allotted to the workers themselves or the technology they use. Because of this large wage gap for similar levels of effort, Indians are incentivized to be part of the US workforce.

Because of the increase in demand for H1B visas, there have been policy changes that cap the number of visas provided. There is some literature on the impact of these changes in policy. Glennon (2020) shows that the H1B visa restrictions by Trump led to high skilled human capital moving to India because of their relaxed immigration policies. These high-skilled workers are mostly Indians who did not receive a continued approval on their H1B visa. This implies that fewer visas can lead to Indian firms retaining more talent. In addition, some evidence suggests that the H1B visa ban by Trump in 2018 led to a decline in the market performance of some Indian IT stocks (Rajamohan & Arivalagan, 2018). Rajamohan & Arivalagan (2018) used a paired sample t-test, however, the methodology does not seem robust because the test does not control for other factors that could affect share prices. Thus, the evidence in this study does not seem to be very compelling, and this thesis intends to provide a more robust analysis.

This thesis has three main contributions to the literature. First, an amelioration of the current, limited literature on the impact of emigration on local firm performance. Second, a consideration of a specific immigration process (H1B visas) that directly impacts the Indian high skill labor market and firm performance. Last, an implementation of recent data and models that can be emulated for similar studies in different regions or time periods.

## 3 Data Description

This section describes the dataset by explaining the rationale behind each variable followed by a summary of their definitions and descriptive statistics. Additionally, this section provides an explanation of how the sample was picked, and where the data was sourced from.

### 3.1 Dataset Overview

The dataset used is a panel with 1352 observations, 104 Indian firms with 13 years of data for each firm from 2009 to 2021. The firms have been selected on the basis of the highest market capitalization in each industry. Firms that did not have data for the entire 13-year time period were removed. The panel is balanced, or has complete data across all 13 years. Firms are classified by NAICS industries, and the categorical variables that describe each datapoint are defined in Table 3.1. The benefits of using such a panel is described in the Methodology section of this thesis.

Table 3.1: Definitions of Categorical Variables

| Variable | Definition |
|---|---|
| **Firm Name** | Name of the Indian firm listed on either the National Stock Exchange of India (NSEI or NSE) or the Bombay Stock Exchange (BSE) |
| **Year** | Year of data in question |
| **NAICS Industry** | The industry classification of the Indian firm according to the North American Industry Classification System (NAICS) |
| **NAICS Code** | The code of the NAICS industry classification |

NAICS industries were initially part of the H1B visa dataset from the USCIS H1B Employer Data Hub. According to the US Census Bureau (2022), NAICS is the standard used by Federal statistical agencies in classifying firms. It classifies firms into industries according to similarity in processes used to produce goods or services (ibid.). These industry classifications are mainly used by the US, and Indian firms are not typically categorized by them. But to control for industry wide variation, it was crucial to classify Indian firms by these industries. Therefore, the sample selection process revolved around the NAICS industries

Many Indian firms in the dataset are conglomerates that do not specialize in a single industry, i.e., more than one of the NAICS industries could apply to such firms. To mitigate these complications, this thesis considered the largest business segment of the conglomerates when picking their most relevant NAICS industry. Firms that are not conglomerates and focus on a specific business line were classified based on the similarity between their business line and the NAICS industry description. The data of the 18 NAICS industries considered and number of firms in each industry is summarized in Table 3.2.

Table 3.2 suggests that each industry has an average of about 6 firms with a standard deviation of about 2.5. The sample is balanced enough to control for the effects of each industry. The only industries which might not be represented well enough are Administrative and Support and Waste Management and Remediation Services, and Retail Trade because they have 3 observations, which is a little more than one standard deviation from the mean. Their underrepresentation is a result of the fact that there aren’t enough publicly traded firms in India that have data from 2009 to 2021 in these industries. Manufacturing on the other hand has 14 firms in the sample. This is because the main function of most of the conglomerates mentioned earlier is closest to the NAICS description of Manufacturing.

Table 3.2: Number of Indian Firms in Each NAICS Industry

| Industry | NAICS | # Firms |
|---|---|---|
| Accommodation and Food Services | 72 | 5 |
| Administrative and Support and Waste Management and Remediation Services | 56 | 3 |
| Agriculture, Forestry, Fishing and Hunting | 11 | 5 |
| Arts, Entertainment, and Recreation | 71 | 4 |
| Construction | 23 | 6 |
| Educational Services | 61 | 5 |
| Finance and Insurance | 52 | 9 |
| Health Care and Social Assistance | 62 | 5 |
| Information | 51 | 5 |
| Management of Companies and Enterprises | 55 | 4 |
| Manufacturing | 31 | 14 |
| Mining, Quarrying, and Oil and Gas Extraction | 21 | 7 |
| Professional, Scientific, and Technical Services | 54 | 6 |
| Real Estate and Rental and Leasing | 53 | 5 |
| Retail Trade | 44 | 3 |
| Transportation and Warehousing | 48 | 5 |
| Utilities | 22 | 6 |
| Wholesale Trade | 42 | 7 |
| Total | | 104 |

## 3.2 Indian Firm Performance

The dependent variable of the hypothesis is Indian firm performance. A firm's performance can be described in in two ways: market performance or accounting profitability. Market performance does not tell us about the fundamental value of a firm, but it indicates the market's perception of that value. Researchers that employ market performance should focus on how firm strategies influence investors' perception (Gentry & Shen, 2010). Accounting profitability, on the other hand, tells us about the ability of a firm to generate profits from its operations over a period of time. This thesis assumes that when Indian firms lose skilled workers to the H1B visa program, they have less workers that can maintain the same level of operational effectiveness. This level of effectiveness is intrinsic to the firm, independent of the market's perception.[1] So accounting profitability is a more precise tool to measure Indian firm performance than market performance.

Return on assets (ROA), defined in Table 3.3, is an accounting profitability ratio, calculated by dividing a company's income by its total assets, that measures how efficiently a company can turn a profit from the assets it chooses to invest in. It captures business fundamentals holistically by considering both the income statement performance and assets used to run the business (Hagel III & Brown 2013). Other financial ratio's such as return on equity are vulnerable to financial engineering, especially through debt leverage, which can obscure business fundamentals (ibid.). By considering long term assets, such as property, plant, and equipment, and intangibles, that are difficult to tamper with compared to shorter term income statement items, ROA is less vulnerable to tampering (ibid.). Thus, this thesis employs ROA as the accounting profitability ratio to measure Indian firm performance, the dependent variable.

Table 3.3: Definition of the Dependent Variable, Return on Assets (ROA)

| Dependent Variable | Definition |
|---|---|
| **ROA (Return on Assets)**[2] | A financial ratio calculated by dividing earnings by total assets. This thesis uses ROA to measure Indian firm performance |

As seen in Figure 3.1, the average ROA for most industries is fluctuating between -0.1 and 0.1 from 2009 to 2021. However, there are a few industries that have more pronounced ROA fluctuations, namely Educational Services, Professional, Scientific, and Technical Services, and Wholesale Trade. The ROA of these industries fluctuate between 0 and 0.2 from 2009 to 2021. The industries with the least ROA fluctuations from 2009 to 2021 are Finance and Insurance,

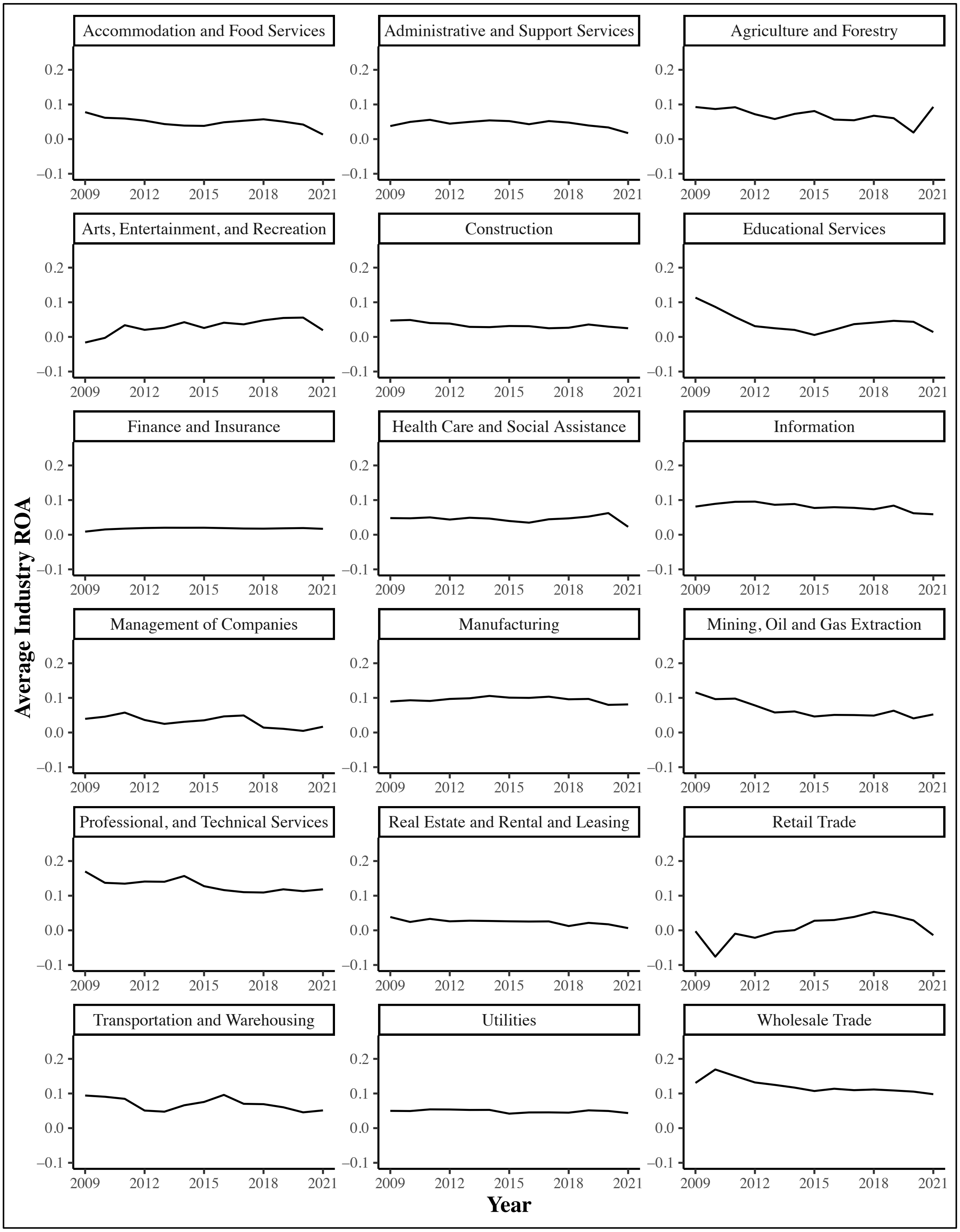
[1] While both accounting and market performance measures are positively correlated across industries, their covariance is less than 10% and there is no evidence of convergence (Gentry & Shen, 2010).

[2] ROA is traditionally calculated using earnings, but this thesis uses operating ROA. Operating ROA uses EBIT (earnings before interest and taxes) instead of earnings.

Utilities, Manufacturing and Construction. On the other hand, the industries with the highest fluctuations are Arts, Entertainment, and Recreation, Agriculture and Forestry, and Retail Trade. Note that although average industry ROA is presented in Figure 3.1, this thesis does not consider industry ROA in the models described in the Methodology section. Instead, firm level ROA is used to test the hypothesis, and it fluctuates more than the average industry ROA over time.[3]

[3] Figure 3.1 depicts industry ROA over time and is only presented to give the reader an understanding of how firm ROA fluctuates over time on average. Also, the names of some industries have been shortened to fit the figure. Refer to table 3.2 for the full industry names.

Figure 3.1: Average Industry ROA from 2009 to 2021



## 3.3 H1B Visa Demand

The independent variable of interest in this thesis is the demand for H1B visas in the US. It can be thought of as both the demand for foreign high-skilled workers from US firms, and the demand from these workers for H1B visas. The variables related to H1B visa demand are defined in Table 3.4. If a US employer wants to employ an Indian worker, they must submit a petition to the USCIS. The USCIS then decides whether or not to approve the petition and move the applicant into the lottery. This thesis uses the number of petitions that the USCIS approves as a proxy variable for the demand for H1B visas in the US. Not only does this variable tell us the demand coming from Indian workers, but also from US firms. One of the shortcomings of using approvals is that they are representative of demand for H1B visas from all countries, not just India. However, 74.1% and 74.9% of H1B visa applications approvals in 2021 and 2022, respectively, are from India (Kably, 2022). So even though approvals is not specific to India, it is strongly indicative of demand from India.

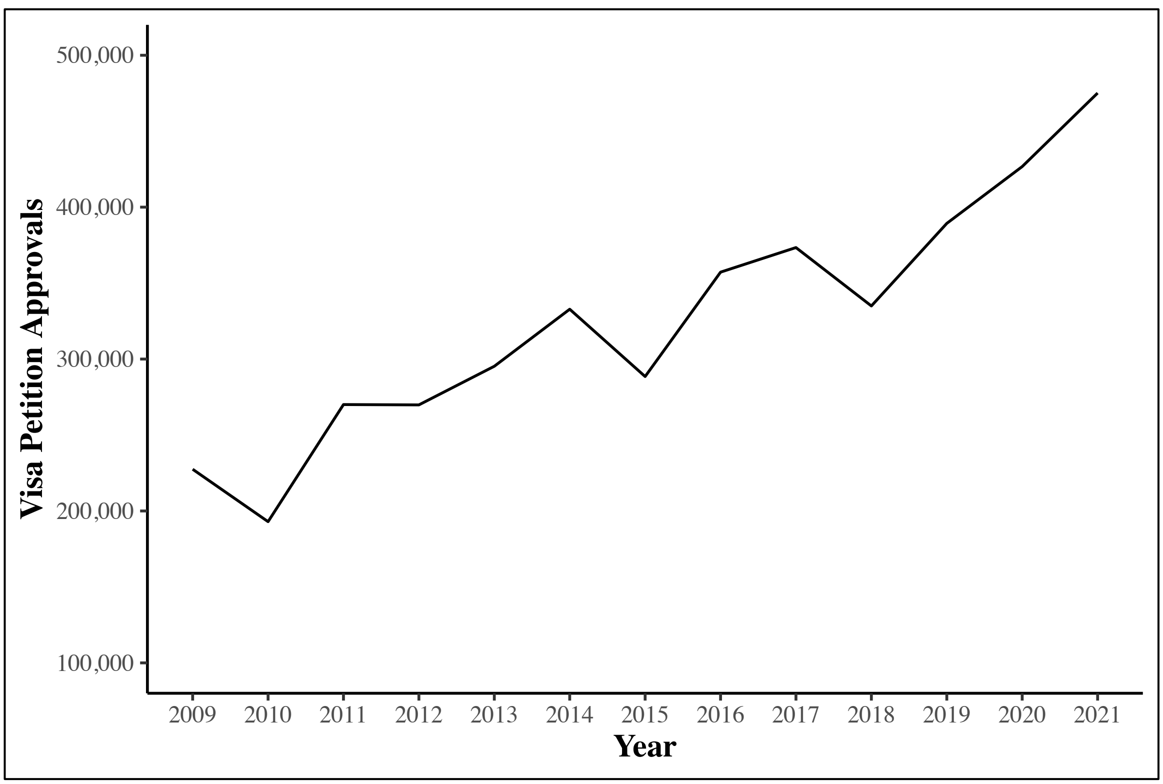
Table 3.4: Definitions of H1B Visa Variables

| H1B Visa Variable | Definition |
|---|---|
| **Approvals** | The number of employer H1B petitions the USCIS approves to move forward to the visa lottery. This thesis uses Approvals to measure H1B visa demand |
| **Denials** | The number of employer H1B petitions the USCIS denies to move forward to the visa lottery |
| **Applications** | The number of employer H1B petitions the USCIS receives |

The hypothesis hinges on the premise that Indian firm performance suffers from losing skilled workers to US firms. Consider two types of visa applicants: (type 1) one that switches jobs from an Indian firm to a US firm, and (type 2) another that begins their career in the US after an MBA. Type 1 applicants would affect Indian firm performance more directly than type 2. Over time, a large number of type 2 applicants could result in the number of high skill workers India reducing, thereby affecting Indian firm performance. Approvals does not account for these differences in applicants. It would, of course, be helpful to have variables that account for these differences, however, such data is not readily available.

An alternative variable to capture H1B visa demand would be the number of applications to obtain a work visa for a skilled non-US worker. These applications are essentially the petitions submitted by US employers to the USCIS. Two of the conditions for a petition to be approved are that the job must require specialized knowledge, and there is a lack of qualified US applicants for that job. So applications might include people who are not actually skilled workers that have specialized knowledge in their occupational field. Approvals discards these workers, and is therefore a better proxy than applications for the demand of high skilled Indian workers. Total number of visa petition approvals from 2009 to 2021 is shown in Figure 3.2.

Figure 3.2: Visa Petition Approvals from 2009 to 2021



As mentioned in the literature review and hypothesis development section of this thesis, the total number of visa approvals has increased significantly over time. This can be seen in Figure 3.2. There were 475,123 visa approvals in 2021 compared to only 227,477 in 2009. There were a few hiccups in 2010, 2015, and 2018 where we see a decrease in the number of approvals. However, the overall trend is strongly positive and consistent with the literature. Because the values for approvals are large and strictly positive, the natural log of approvals has been used in the models described in the Methodology section later in this thesis.

### 3.4 Control Variables

ROA can be affected by variables other than approvals, so the control variables used to test the hypothesis are the market capitalization of Indian firms and the index returns of the industry that the Indian firm is in. Market capitalization controls for the size of the firm, whereas index returns controls for the effects of the firm's industry. These variables are defined in Table 3.5.

Table 3.5: Definitions of Control Variables

| Control Variable | Definition |
|---|---|
| **Market Capitalization** | The dollar value of a firm's equity or firm value. This thesis uses Market Capitalization to control for firm size |
| **Index** | The market index of the industry that the firm belongs to. This thesis uses 11 such indices. |
| **Index Price** | The price of the index measured by S&P Global Ratings |
| **Index Returns** | The annual returns of the index. This thesis uses Market Capitalization to control for industry effects |

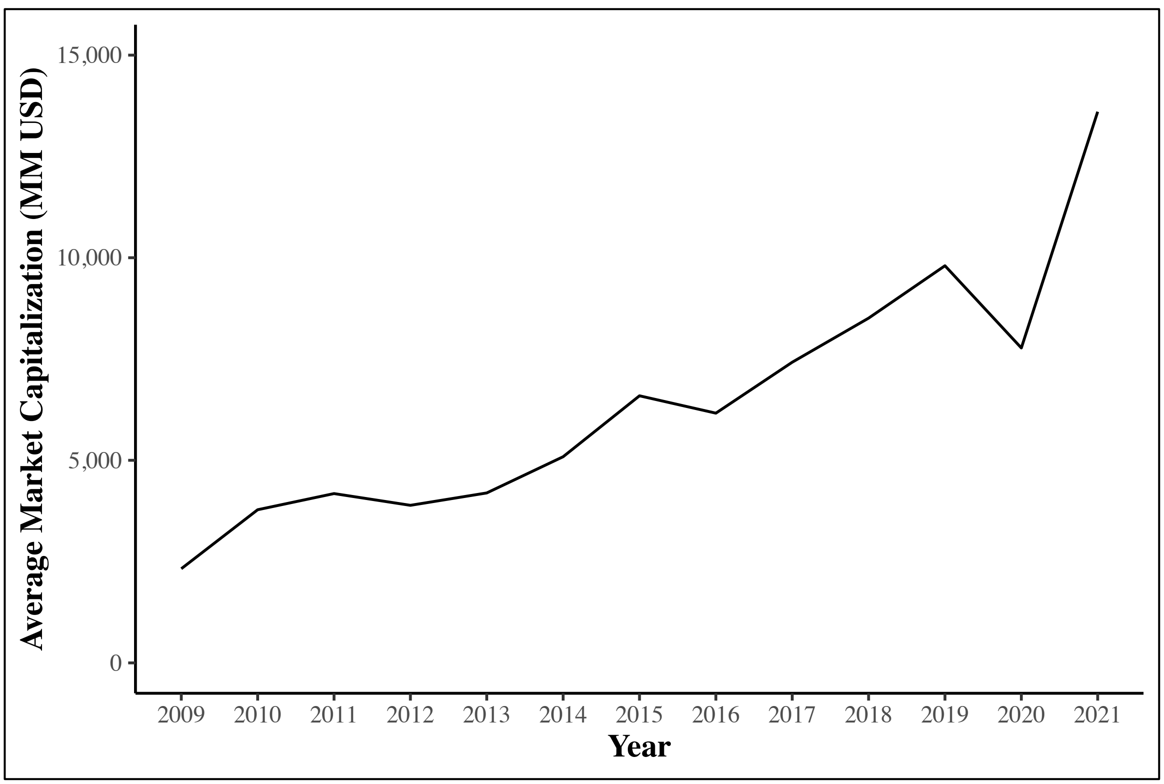
Firm size is important because of it can be correlated with profitability. Bigger firms are capable of generating a larger amount of goods and services compared to smaller firms because they have the ability to achieve economies of scale. Research on Indian firms reveals that firm size has a positive association with firm profitability (Homaidi et al., 2021). The study considers a panel of 1,308 firms listed on the Bombay Stock Exchange (BSE), and uses recent data from 2011 to 2018. Moreover, it uses fixed effect models, which provides its field of research with evidence using different statistical analysis from previous studies.

For the purpose of this thesis, firm size would ideally refer to the number of employees at the Indian firm. The motivation is based on the fact that if an Indian firm has a large number of employees, the effect of losing an employee to a US firm (because of the H1B visa program) might not be as large as that for a smaller firm. Market capitalization is the total dollar value of a publicly traded firm (Ewing & Thompson, 2016). Although market capitalization does not directly measure the number of employees, the two are positively correlated. Research suggests that when data about number of employees is not available, market capitalization can be used instead (Dang et al., 2018). However, a more precise control would be the number of employees. Because of data limitations this thesis could not use the number of employees as a control.

Regressions that use different firm size measures to predict firm performance usually achieve coefficients with the same sign, but the magnitude of these coefficients is sensitive to the choice of firm size (ibid.). Different measures capture different aspects of firm size, thereby having different implications in corporate finance (ibid.). The three most popular measures of firm size are total assets, total sales, and market capitalization (ibid.). This thesis cannot employ total assets because the dependent variable, ROA, is linearly related to the reciprocal of total assets (ROA is earnings divided by total assets). Total sales, similarly, is captured by the earnings aspect of ROA. However, market capitalization is not nearly as closely related to ROA compared to the other two measures. It is forward looking because it is an estimation of the present value of future cash flows of a company. Therefore, this thesis uses market capitalization as a control variable for firm size.

The average market capitalization for the Indian firms in the dataset is increasing every year. Figure 3.3 shows the average market capitalization in millions of USD each year. Note that the first year of data is right after the 2008 financial crisis and the drop in 2020 is a result of the Covid-19 pandemic. This suggests that firm size is increasing over time, and there are probably more employees (the ideal variable) in the workforce, although it is unlikely that the number of employees is increasing at the same rate. Because the values for market capitalization are large and strictly positive, the natural log of market capitalization has been used in the models described in the Methodology section later in this thesis.

Figure 3.3: Average Market Capitalization (MM USD) from 2009 to 2021

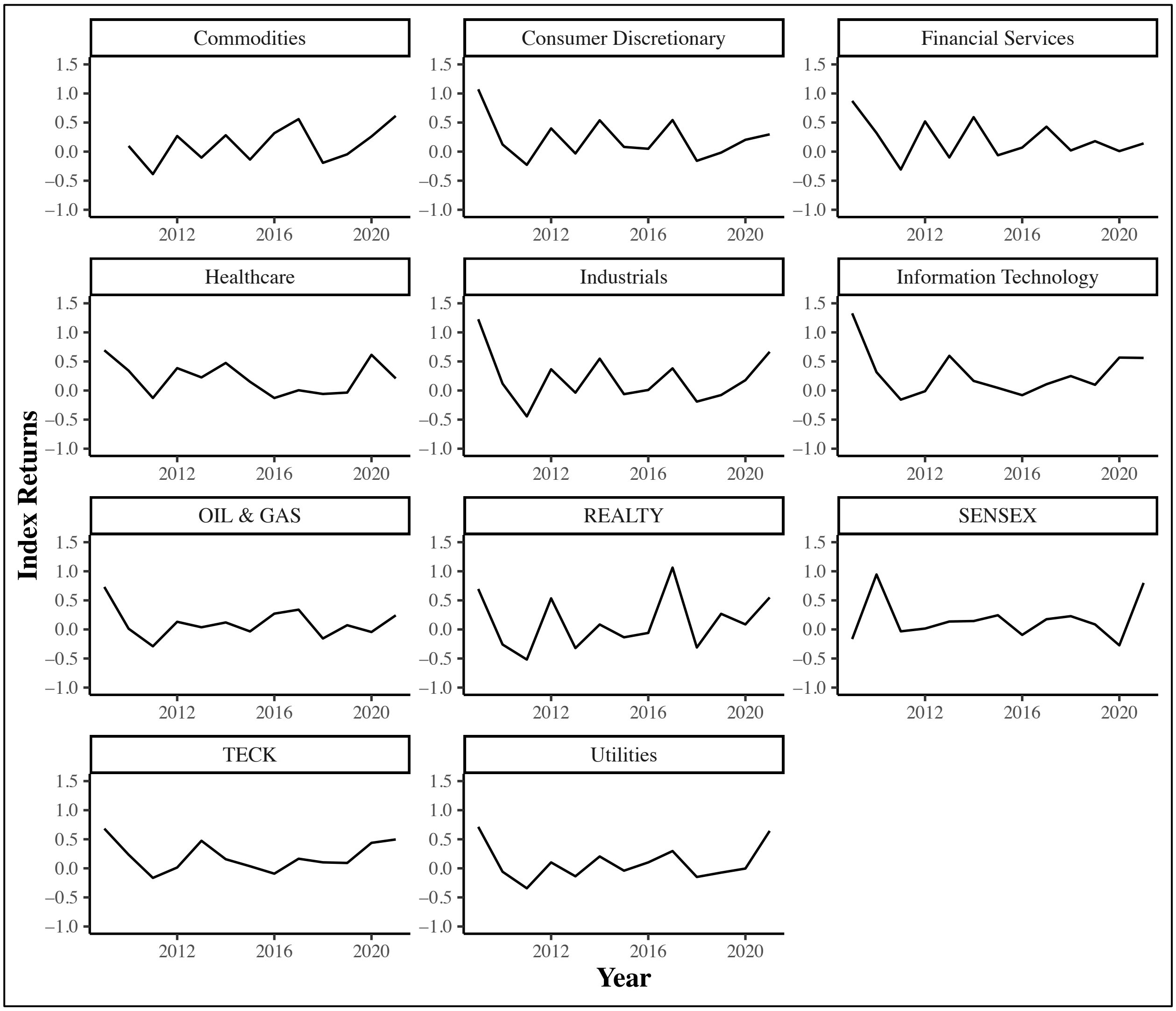



Apart from firm size, another firm characteristic that impacts performance (profitability) is the industry that the firm is in: more specifically, the effect of being part of a certain industry and the performance of the industry. Rumelt's study in 1991 is considered to be the most influential in determining industry effects on firm performance (McGahan & Porter, 1997). He shows that industry effects significantly impact ROA by extending approaches used previously (ibid.). More current literature, similarly, suggests that a significant portion of the relative degree of variance across firms' ROA is accounted for by the industry of the firm (Roquerbert et al. 1996).

When Rumelt's models were revisited using McGahan & Porter's more recent data, the results remained very similar (Brush, Bromiley, Hendrickx, 1999). Furthermore, McGahan & Porter also refined Rumelt's models to find that this variation differs among industries; for example, industry effects explain a smaller portion of variation in ROA for firms manufacturing firms, but a larger portion in transportation, entertainment, wholesale trade, retail trade, and lodging firm (McGahan & Porter, 1997). However, the variation still exists and the firms' industries evidently have a strong direct and indirect impact on firm profitability (ibid.). The studies mentioned above use industry ROA to measure industry effects. Due to data limitations, this thesis uses returns on the price of the BSE index belonging to the firm's industry instead of industry ROA.

The existing BSE indices do not exactly match the NAICS industries, so the indices closest to the NAICS industry description have been picked to represent that industry. Table 8.1 in the Appendix shows how the closest BSE index has been picked for each NAICS industry. Figure 3.4 shows the returns for each of the BSE indices. Index returns seem to be fluctuating differently for each of the industry specific indices. SENSEX is a market index of the 30 most established firms in the BSE, and TECK is an index that comprises of firms in the media, telecommunications, and information technology industry. The returns for each of the indices are mostly fluctuating in the same direction but at varying magnitudes.

Figure 3.4: S&P BSE Index Returns from 2009 to 2021




Although firm size (market capitalization) and industry effects (index returns) are crucial control variables, numerous studies prove that the core business of the firm is the most significant driver of firm performance (McGahan & Porter, 1997, Roquebert et al., 1996, Brush, Bromiley, Hendrickx, 1999, Arend, 2009). The fixed effects model employed to test the hypothesis inherently controls for firm fixed effects. The mechanism behind this is explained in the methodology section of this thesis.

### 3.5 Data Sources

The Indian firm data, ROA, and market capitalization, has been collected from the S&P Capital IQ database. This data is from both the Indian stock exchanges: BSE and NSE. The H1B visa data, approvals, denials, and applications, has been collected from the USCIS H1B Employer Data Hub. The index data, index, and index price, has been collected from the Bombay Stock Exchange database.

## 4 Methodology

This section first explains the advantages and limitations of using panel data. It then describes the fixed effects model that this thesis uses to test the hypothesis that H1B visa demand impacts Indian firm performance negatively.

### 4.1 Advantages and Limitations of Panel Data

The panel dataset can be analyzed using a fixed effects model that controls for individual (Indian firm) heterogeneity. Cross-sectional and time-series models that do not control for heterogeneity run the risk of obtaining biased results (Baltagi, 2015). The panel dataset used in this thesis considers the impact of H1B visas using two dimensions: Indian firms effects and time effects. These effects cannot be measured together using pure cross-sectional or pure time-series data. According to Baltagi (2015), panel datasets provide more variability, less collinearity among variables, more degrees of freedom and more efficiency than most time-series and cross-sectional datasets (ibid.).

The limitations stated by Baltagi (2015) relate to issues in data collection. These include measurement errors, selectivity problems (such as nonresponses and attrition), and having a short time-series dimension. These issues are mostly found in surveys and other forms of data relating to human behavior. This panel dataset used in this thesis is not burdened by these challenges in data collection because the data has been collected from reliable sources with complete data. A potential issue pointed out by Baltagi (2015) is cross-section dependence (or contemporaneous correlation). This means that there might be cross-firm dependence, but it usually exists in macro panels with 20 to 30 years of data. The panel used in this thesis more closely resembles a micro panel with fewer years of data (13) over a larger number of cases (104).

### 4.2 Model Specification: The Fixed Effects Model

Generally, a panel data regression is different from a time-series or cross-section regression because there is a double subscript on the variables (Torres-Reyna, 2007). The fixed effects model equation is

$$y_{it} = \alpha + X'_{it}\beta + \mu_i + \lambda_t + v_{it} \tag{1}$$

where index $i$ denotes the 104 Indian firms, i.e., $\{i \in \mathbb{Z} \mid 1 \leq i \leq 104\}$. Index $t$ denotes the 13 years from 2009 to 2021, i.e., $\{t \in \mathbb{Z} \mid 1 \leq t \leq 13\}$. Thus, the $i$ subscript is representative of the cross-sectional dimension (Indian firms), whereas the $t$ subscript is representative of the time-series dimension (year). $y_{it}$ is the dependent variable (ROA) of the $it$th observation. $\alpha$, a scalar, is the intercept. $\beta$ is a $Kx1$ vector of coefficients and $X_{it}$ is the $it$th observation on $K$ explanatory variables (Baltagi, 2015). So $X_{it}$ contains the independent variables such as approvals, market capitalization, and/or index returns, i.e., $\{K \in \mathbb{Z} \mid 1 \leq K \leq 3\}$. Each entry in the $\beta$ vector measures the effect of one of these independent variables on $y_{it}$ (ROA). $\mu_i$ denotes Indian firm fixed effects, or unobservable time-invariant firm characteristics. $\lambda_t$ denotes time (year) fixed effects that captures unobservable aggregate shocks or macroeconomic factors that cause ROA to vary across each year, but not across Indian firms. $v_{it}$ is the error term that varies with both Indian firms and time, and captures time-varying unobservable effects that impacts ROA.[4] The salary of the Indian firm's CEO is an example of something that $v_{it}$ captures.

### 4.3 Model Estimation: Dummy Variable Regression

To estimate the fixed effects model, a dummy variable regression is used. In equation (1), $\mu_i$ is a set of dummy variables for each Indian firm $i$ (omitting the first one in the dataset), and $\lambda_t$ is a set of dummy variables for each year $t$ (omitting 2009). This model is then estimated using Ordinary Least Squares (OLS).

### 4.4 Model Discussion

As mentioned earlier, $\mu_t$ and $\lambda_i$ account for Indian firm specific effects and time specific effects, respectively, that are unobservable. Stock & Waston (2019) say that the insight behind the unobservable variables is that if they do not change over time, then changes in the dependent variable (ROA) must be a result of influences other than the fixed.

Each firm has their own characteristics that might influence the dependent variable, ROA. One of the assumptions of fixed effects is that something within Indian firms that does not change over time may impact or bias the dependent variable and it must be controlled for using the $\mu_i$ term in equation (1) (Torres-Reyna, 2007). By removing the effects of these time invariant characteristics, fixed effects allows for an assessment of the net effect the predictors have on the dependent variable (ibid.).

Panel data can also be analyzed using a random effects model, but such models have a strong assumption. Random effects assumes that the individual effects are a random variable that are uncorrelated with the error term. This suggests that any time-invariant Indian firm

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[4] Note that the difference between $\lambda_t$ and $v_{it}$ is that $\lambda_t$ captures unobservable firm-invariant time fixed effects, whereas $v_{it}$ captures unobservable firm and time varying effects.

characteristics are unrelated to unobservable effects that impact firm ROA. This assumption likely does not hold for the panel dataset in question, so this thesis employs a fixed effects model instead.

## 5 Results

This section showcases and describes the results of using the fixed effects model on the panel dataset described in the Data Description section of this thesis. The aim of this model is to test the hypothesis that demand for H1B visas in the US impacts the performance of Indian firms negatively.

### 5.1 Initial Results

A total of four regressions have been used to test the hypothesis. The equations for the four regressions are the same as (1) in the Methodology section. All the regressions include both firm and year fixed effects, but the independent variables in the $X$ matrix vary. The differences in the independent variables of each of the four models are summarized in Table 5.1. Note that lapprovals is the natural log of approvals, lmktcap is the natural log of market capitalization, and index_returns are the yearly returns of the industry index.

Table 5.1: Fixed Effects Models

| Model | Independent Variables (other than firm fixed effects and time fixed effects) |
|---|---|
| **1** | lapprovals |
| **2** | lapprovals, lmktcap |
| **3** | lapprovals, index_returns |
| **4** | lapprovals, lmktcap, index_returns |

The results of the models listed in Table 5.1 are shown in Table 5.2. Model (1) is the best quality model (explained in the robustness section below) and it confirms the hypothesis, which predicted that Indian firms lose skilled workers because of the H1B visa program and this loss in skilled labor leads to a decline in Indian firm performance. However, the impact on Indian firm performance is of a small magnitude. More precisely, a 1% increase in H1B visa approvals is associated with a predicted decrease of ROA by -0.01 percentage points. Moreover, the 90% confidence interval for the results does not contain zero.

Table 5.2: Results for Models (1), (2), (3), and (4)

| Model | (1)<br>ROA | (2)<br>ROA | (3)<br>ROA | (4)<br>ROA |
|---|---|---|---|---|
| lapprovals | -.01* | -.009* | -.01* | -.009* |
| | (.005) | (.005) | (.005) | (.005) |
| lmktcap | | .004* | | .004* |
| | | (.002) | | (.002) |
| index_returns | | | .007 | .007 |
| | | | (.005) | (.005) |
| _cons | .135*** | .094** | .128*** | .087* |
| | (.039) | (.045) | (.039) | (.045) |
| Observations | 1352 | 1352 | 1352 | 1352 |
| Firm Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| R-squared | .543 | .544 | .543 | .545 |
| BIC | -4298 | -4295 | -4293 | -4290 |

*Standard errors are in parentheses*
**** p<.01, ** p<.05, * p<.1*

An increase in H1B visa approvals can be thought of in two ways. First, it can be looked at from the lens of US employers that want to hire more international high skilled workers. Second, it can be looked at from the lens of international high skilled workers that have a desire to pursue a career in the US. The literature suggests that about 74% of the international skilled workers in question are from India (Kably, 2022). The US employers want to hire them because there aren't any locals that have the same ability. The Indian workers are likely to prefer working in the US because they receive much higher pay for the same job. In essence, a larger number of H1B visa approvals leads to a shift of high skilled workers from India to the US. As high skilled Indian workers leave the Indian workforce, the results of the regression suggest that there is a negative impact on Indian firm performance.

## 5.2 Robustness

The quality of the models was tested using Bayesian Information criterion (BIC). A study by Yum (2021) uses Monte Carlo experiments to show that applying BIC to panel data models with fixed effects is quite successful in selecting the true model. The lower (more negative) the BIC, the more preferable the model (Schwarz, 1978). As seen in Table 5.2, model (1) has the most negative (lowest) BIC, which is why it is considered the best quality model.

The model is robust because the results are consistent even as the matrix of independent variables $X$ is changed. Table 5.2 shows that the coefficient for lapprovals is about -0.01 or (-0.009) and the 90% confidence interval for the results does not contain zero across all four models. Similarly, the coefficients for lmktcap in, both, models (2) and (4) are 0.04 and significant. Although the coefficient for index_returns is not significant, the value itself, 0.007, is consistent in models (3) and (4).

Model (2) is the second most preferred model among the 4. Since the coefficient for lapprovals is very similar to that in model (1) its interpretation remains the same. The coefficient for lmktcap is positive, thus it aligns with the literature that as firm size increases they have better performance. More precisely, a 1% increase in market capitalization is associated with a predicted increase in ROA of 0.004 percentage points.

Model (3) involves market returns, which does not seem to have a significant impact on ROA. Model (4) looks like a combination of models (2) and (3) because the coefficient for lmktcap is very similar to that in model (2) and the coefficient for index_returns is very similar to that in model (3). However, it has the least negative (highest) information criteria among the 4 models, which is why it has been ruled out.

### 5.3 Alternative Study

Former US President Donald Trump signed an executive order in 2017 called "Buy American, Hire American." This order made the rules for H1B visas more stringent by ensuring that visas would only be awarded to those that are the "most-skilled" and "highest-paid" (Exec. Order No. 13788, 2017). What followed from this was a decline of H1B visa petition approvals in 2018 as seen in Figure 3.2. Additionally, amid the Covid-19 pandemic, Trump issued another order that temporarily suspended entry into the US and restricted issuance of visas for several immigrant categories, including H1B visas (Shear & Jordan, 2020). In essence, H1B visas were faced with a large amount of resistance during the Trump's presidency. He claimed that the goal was to protect the jobs of US nationals, and made efforts to dissuade US employers from hiring high skilled international workers.

To measure the impact of Trump's policies, this thesis considered an alternative model which compares the impact of approvals on ROA during the time Trump was President to when he wasn't. If Trump's orders were successful fewer Indian workers would receive H1B visa approvals. Thus, Indian firms would lose a smaller portion of their high skilled labor, and their ROA would not be affected as much.

The model (5) used is a fixed effects model with the equation (1), however, the independent variables in the $X$ matrix are different from models (1) to (4). Instead of using lapprovals as the independent variable of interest, two variations of lapprovals are used in this model. The first is trump_lapprovals, which is the natural log of H1B visa approvals from 2017 to 2020. This is the Trump era, or the period during Trump's presidency after he issued the first order that made the H1B visa process more stringent. The second is non_trump_lapprovals, which is the natural log of H1B visa approvals from 2009 to 2016 and 2021. This is the non-Trump era, or the period when

Trump was not President (2009-2016), and President Joe Biden reversed the H1B visa restrictions imposed by Trump (2021). In essence, the alternative model measures the impact of lapprovals on ROA in two different time periods: $t_{trump} = \{2017, \ldots, 2020\}$ and $t_{non\_trump} = \{2009, \ldots, 2016, 2021\}$. The results of the model are shown in Table 5.3 below.

Table 5.3: Results for Model (5)

| ROA | Coef. | St. Err. | t-value | p-value | [95% Conf. | Interval] | Sig. |
|---|---|---|---|---|---|---|---|
| trump_lapprovals | -.01 | .005 | -1.98 | .047 | -.02 | 0 | ** |
| non_trump_lapprovals | -.012 | .005 | -2.30 | .022 | -.023 | -.002 | ** |

| | | | |
|---|---|---|---|
| Mean dependent var. | 0.061 | SD dependent var. | 0.070 |
| R-squared | 0.543 | Number of observations | 1352 |
| F-test | 12.548 | Prob > F | 0.000 |
| Firm Fixed Effects | Yes | Time Fixed Effects | Yes |
| Akaike crit. (AIC) | -4165.870 | Bayesian crit. (BIC) | -3551.168 |

**** p<.01, ** p<.05, * p<.1*

The results for the alternative model show that a 1% increase in H1B visa approvals during the Trump era is associated with a predicted decrease of ROA by -0.01 percentage points. Whereas, a 1% increase in H1B visa approvals during the non-Trump era is associated with a predicted decrease of ROA by -0.012 percentage points. The coefficients for trump_lapprovals and non_trump_lapprovals are nearly identical and fall into each other's confidence intervals. This implies that there is no significant difference between the impact of H1B visa approvals on ROA in the two time periods: Trump era and non-Trump era. In essence, the hypothesis that Indian firm ROA would be impacted less during the Trump era cannot be confirmed by these results. However, the results do suggest that Trump's orders were not very successful in making US employers respond to a more difficult H1B visa process.

## 6 Conclusion

A firm's performance is heavily dependent on the skill level of its employees. To maintain a strong workforce of such skilled employees, firms must provide them with adequate compensation. If employees believe that they can receive better compensation elsewhere, they would be inclined to switch jobs. Compared to India, the US offers significantly better compensation for highly skilled employees. This is why the demand for H1B visas is drastically increasing every year. Figure 3.2 shows how much the demand for these visas has risen since 2001. It is clear that highly skilled Indian workers have a strong desire to immigrate to the US. Indian firms lose some of these high skilled workers as result, which, as this thesis shows, impacts their performance.

By considering a firm-level panel dataset, this thesis investigated the impact of the demand for H1B visas on the performance of Indian companies. The panel allowed the use of a fixed effects model, which helped control for unobservable time invariant characteristics of firms that a regular cross-sectional or time-series dataset could not do. The results confirmed the hypothesis that Indian firm performance is negatively impacted by an increase H1B visa demand.

These results must be used by Indian firms to retain high skilled labor. Although the wage gap is large, the cost of living in the US is also much higher than that in India. Thus, firms do not have to strive to bridge the entire wage gap, but they must try to match salaries by accounting for the cost of living. Closing the wage gap is a very difficult solution, and might not be practical for every job in a developing like India. But some jobs that have a very high skill barrier, such as software development jobs, should try and reach this goal. Moreover, firms could benefit from using their human resources departments to strategically create retention measures.

While labor retention strategies from firms might help prevent some high skilled employees from leaving India, they are a short term solution. In the longer run, policymakers must intervene by creating measures to improve the skill level of the labor force. Firms are usually burdened with high training costs. The government could provide training courses specific to some high skilled jobs to alleviate some of this burden off firms. In addition, the education system should be more geared towards the demands of the labor market. The friction arising from a loss of skilled labor can be mitigated from its roots if such measures are in place.

The current emigration policies implemented in India revolve around lower-skilled workers that migrate to the surround Gulf countries. The reason for this is that most of the emigrant population is low-skilled or medium-skilled. Additionally, these workers are often subject to exploitation in these countries. So the Emigration Act, 1983 and The Draft Emigration Bill 2019 aim to protect these workers. The Indian government should, of course, protect such Indian emigrants as their first priority. However, the solutions listed in this section do not ask for reform in regard to these policies.

## 7 References


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# 8 Appendix: NAICS Industries Mapped to S&P BSE Indices

Table 8.1

| S&P BSE Index | Industry | NAICS |
|---|---|---|
| Commodities | Agriculture, Forestry, Fishing and Hunting | 11 |
| Consumer Discretionary | Accommodation and Food Services | 72 |
| Consumer Discretionary | Retail Trade | 44 |
| Consumer Discretionary | Wholesale Trade | 42 |
| Financial Services | Finance and Insurance | 52 |
| Healthcare | Health Care and Social Assistance | 62 |
| Industrials | Construction | 23 |
| Information Technology | Professional, Scientific, and Technical Services | 54 |
| Information Technology | Information | 51 |
| OIL & GAS | Mining, Quarrying, and Oil and Gas Extraction | 21 |
| REALTY | Real Estate and Rental and Leasing | 53 |
| SENSEX | Management of Companies and Enterprises | 55 |
| SENSEX | Educational Services | 61 |
| SENSEX | Transportation and Warehousing | 48 |
| SENSEX | Manufacturing | 31 |
| SENSEX | Administrative and Support and Waste Management and Remediation Services | 56 |
| TECK | Arts, Entertainment, and Recreation | 71 |
| Utilities | Utilities | 22 |