Trumping Immigration: Visa Uncertainty and Jobs Relocation*

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Abstract

Exploiting President Trump's win in the Republican Primary election, we estimate the impact of the ensuing uncertainty around H-1B immigration policies on the demand for workers in India. Using postings data from the largest jobs platform in the country, we find that firms more reliant on H-1B visas for filling US-based job positions increase their postings for India-based jobs immediately after Trump's primary win in June 2016. This surge is attributed to heightened outsourcing from the US to India for occupations more amenable to offshoring. Firms headquartered in India lead this change, and subsequently witness an increase in their exports. Our findings reveal that uncertainty around the ability of firms to hire immigrants can have similar deleterious effects as a restrictive immigration policy regime.

JEL Codes: F22, F23, J61, J68

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1 Introduction

In the last decade, heightened anxieties over immigration of both skilled and unskilled workers led to three-to-fourfold increases in migration policy uncertainty (source EPU) across advanced nations – US, UK, France, Germany. In the United States, President Trump's era was characterized by heightened immigration uncertainty. Beginning from his campaign trail to his tenure at the White House, high-skilled immigration, especially the US H-1B visa program, came under attack. For example, during the 2016 Republican debates, President Donald Trump stated his intent to overhaul the H-1B program. "*these are temporary foreign workers, imported from abroad, for the explicit purpose of substituting for American workers at lower pay. I remain totally committed to eliminating rampant, widespread H-1B abuse and ending outrageous practices..*" (The Washington Post). Such statements only intensified after his victory in the Republican Primary in June 2016. Subsequently, as President, he signed the "Buy American and Hire American" executive order of April 2017, which increased Requests for Evidence (RFE) demand from firms seeking H-1B visas. Although there was no change in the quotas for H-1B visas, there was a 91 percent surge in processing times, significantly increasing uncertainty around the successful and timely procurement of these visas. We study the effects of this increased uncertainty (Figure 1, Panel (a)) surrounding H-1B visas after President Trump's victory in the Republican primary on job postings and vacancies by both US (host country) and Indian (sending country) firms.[1]

We investigate the impact of this shock on labor demand in India, a sending country that receives 70 percent of the H-1B visas. We use job listings data from the largest job platform in India, spanning 2014 to 2019, which provides detailed characteristics of job postings, including the job location. Our findings reveal a substantial decline in US-based job postings by firms on the platform, starting immediately after Trump's primary win in June 2016 and persisting through the end of 2019. Furthermore, we find that firms more

[1]Elections can often lead to spikes in policy uncertainty (Canes-Wrone & Park, 2012; Baker *et al.*, 2014, 2020). Such heightened uncertainty can exert a substantial influence on firm-level investment and employment decisions.

reliant on H-1B visas for filling their US-based positions increase job postings for India-based positions in response to the shock. We capture firms' H-1B dependence through their share of US-based postings out of total postings before June 2016. Quantitatively, firms increase their India-based postings by 11.8 percent for every 10 percentage point increase in their H-1B dependence before June 2016.

Next, we conduct multiple tests to ascertain if the offshoring of H-1B dependent jobs to India can explain the observed results. Drawing on the offshorability index of occupations from Blinder *et al.* (2009), we find that occupations more amenable to offshoring witness a greater increase in India-based postings. Moreover, we show that exports of these firms increase by 5.6 percent for every 10 percentage point increase in the treatment intensity, while domestic sales remain unaffected. These findings suggest that the observed increase in India-based job openings is primarily attributable to a shift in jobs from the US to India, rather than an expansion of these firms' operations in India. Additionally, we find that firms headquartered in India are more likely to increase India-based postings after the shock. We also observe spillover effects on other Indian firms, with an increase in postings by firms that had not previously hired for US-based positions, but employed a significant proportion of the workforce in specialty occupations typically associated with H-1B visas.

This study contributes to several strands of literature. First, we add to the discourse on the interplay between immigration and offshoring (Ottaviano *et al.*, 2013; Olney & Pozzoli, 2021; Glennon, 2023). Theoretically, Ottaviano *et al.* (2013) show that immigrants and natives are less substitutable than offshored workers and natives. Glennon (2023) examines the effects of changes in the H-1B visa cap on staffing in foreign country affiliate offices of US firms and finds that employees in these locations increase following a reduction in visa quota. Our study adds to this broader literature by examining the consequences of policy uncertainty on offshoring. We find that firms change their hiring decisions after such shocks, as evidenced by firms' response to Trump's Primary win in our case. Our analysis, therefore, connects the immigration literature with the broader discourse on economic policy uncertainty, which outlines changes in firm decision-making in response to heightened uncertainty (Stein & Stone, 2013; Baker *et al.*, 2016; Gulen & Ion, 2016; Jens, 2017; Faccini & Palombo, 2021). More specifically, our work highlights the spillover effects of immigration policy uncertainty in the host country on labor market outcomes in the sender country.

Second, we contribute to the literature that examines the impact of immigration policies on host country firms and native employment (Mayda *et al.*, 2018; Kerr *et al.*, 2015; Ottaviano *et al.*, 2013; Peri *et al.*, 2015).[2] The evidence in support of immigrants substituting native workers or creating a downward pressure on wages is limited (Borjas, 2005; Bound *et al.*, 2017; Doran *et al.*, 2022; Turner, 2022). Our findings indicate that firms can readily resort to offshoring in response to immigration policy changes, suggesting that an increase in employment in the host country may not materialize for occupations that can be performed remotely. Third, we contribute to the literature that examines the impact on sending countries in the wake of policy shocks. Previous research has largely focused on the effects on skill choice or increased emigration of skilled people from these countries as foreign employment opportunities emerge (Bound *et al.* (2017), see Docquier & Rapoport (2012) for a review). We provide a novel perspective by demonstrating that immigration policy uncertainty could increase demand for skilled labor in the sending country due to a shift in jobs from the host to the sending country (Khanna & Morales, 2017).

Finally, we scrutinize the differential impact on firms headquartered in sending vs. host country. We find that the former set of firms are more likely to offshore, potentially capitalizing on local networks to expedite the transition of US-based jobs to India. This finding underlines the broader point that protectionist measures, rather than fostering domestic gains, may inadvertently be counterproductive (Fajgelbaum *et al.*, 2019).

[2]There is also an emerging literature on the impact of high skilled immigration on firm outcomes. For instance, studies examine the impact on firm level innovation (Ashraf & Ray, 2017; Wu, 2017; Bound *et al.*, 2017), firm employment and structure (Mayda *et al.*, 2018; Doran *et al.*, 2022; Kerr *et al.*, 2015), investment, firm size and labor productivity (Xu, 2018; Ghosh *et al.*, 2014; Ashraf & Ray, 2017).

2 Institutional Details and Chronology

2.1 The H-1B Immigration Scheme

The US provides multiple avenues for hiring foreign high-skilled workers, of which the H-1B visa program is one of the most prominent. It represents nearly half of all temporary work visas, making it the most significant such program.[3] H-1B visas come with an initial validity for 3 years and a potential extension of up to 6 years. Applicants must possess at least a US equivalent bachelor's degree and seek employment in specialty occupations such as technology, finance, engineering, architecture. Indians form the largest pool of the H-1B visa workers. In 2015, U.S. Citizenship & Immigration Services (USCIS) granted $172,748$ H-1B visas, of which $119,952$ (70 percent) were for Indian nationals (Mint, US State Govt Annual Report).[4] See Appendix A.1 for more details.

2.2 Uncertainty in H-1B Visa Policy

During the period of analyses, the H-1B visa cap was limited to 65,000 visas per year which was filled within the first 5-7 days of opening the petitions (RedBus). However, two distinct phases characterize the H-1B policy's uncertainty during our focus period. The first phase begins after Trump's victory in the Republican Primary in June 2016, following which the high-skilled immigration policy under H-1B came into focus. Advocacy for a restrictive visa regime formed a crucial part of his political campaigning. The likelihood of Trump winning the Presidential race, and thereafter his speeches after winning the Presidential elections, increased uncertainty around the H-1B visa policy.[5] Overall, the uncertainty during this

[3] L-1 visa is generally used for intra-company transfers. Others programs include O, OPT, and TN visas.

[4] Around one-third of all the granted visas in 2014 went to the top 13 outsourcing firms. The top recipients among these were Tata Consultancy Services, Infosys and Wipro, all with headquarters based in India. Other US based firms like Microsoft, Intel, IBM, Cognizant and Amazon were also big recipients. These firms typically contract with organizations in other sectors to handle various computing tasks (NYT).

[5] The stance and public statements by Republicans during the campaign period generated more uncertainty around this policy. Reports that Trump stoked outrage from his supporters with examples of firms like Walt Disney firing domestic workers in favor of overseas replacements (NYT).

phase could be attributed to the political uncertainty around the visa regime.

The second phase of this uncertainty commenced with the release of the USCIS document titled "H-1B RFE Standards", on March 23, 2017, contributing to a significant increase in expensive and time-consuming Requests for Evidence (RFEs).[6] In April 2017, President Trump issued the first public directive against H-1B visas with the "Buy American and Hire American" executive order, stressing that the H-1B visas "should include only the most skilled and highest-paid applicants and should never, ever be used to replace American workers." The order mandated greater coordination across government departments for investigation and, if necessary, prosecution of employers who abuse the H-1B program by discriminating against US workers. Unlike previous changes in H-1B visa policy, this escalation of RFEs added a layer of uncertainty to the visa process without altering the annual H-1B visa cap.

We find that discussions on H-1B policy picked up during this period in the media. Figure 1, Panel (a), plots the Economic Policy Uncertainty Index around migration (EPU). Clearly, the uncertainty picked up after Trump's win in the Primary election and further spiked after the signing of the directive.[7]

As a consequence of the directive, recruitment and hiring times increased under the H-1B along with increased probability of rejection. The yearly figures for the proportion of H-1B applications which received a RFE spiked after 2017 (Appendix Figure B.1, Panel (a)). The percentage of completed H-1B cases with a RFE more than doubled from 17 percent in August 2017 to 56 percent by December 2017. In 2014, the average rate was 23 percent. On the other hand, the percentage of H-1B petitions denied for initial employment increased to 24 percent in FY 2018, while between FY 2010 and 2015, the denial rates for H-1B petitions for initial employment were between 5–8 percent (Forbes; see Appendix Figure B.1, Panel (b)). Also, the processing time increased by 91 percent in 2018 since 2014 (National Foundation for American Policy reports). Finally, in July 2019, with the increasing clamour for repealing

[6]Under federal law, employers that use a large number of H-1B workers are supposed to document that they tried to hire Americans for the jobs. This is referred to as Request for Evidence.

[7]Also see Law & Zuo (2022) and Bai *et al.* (2023) for discussion on migration fear index from EPU.

the changes in the H-1B rules, all the regulatory amendments were lifted as Judge Collyer invalidated key USCIS memos and policies that caused the H-1B denial rates to skyrocket. To summarize, while there was no change in H-1B visa cap at $65,000$, the post June-2016 is characterized by heightened immigration policy uncertainty.

3 Data

We use an exclusive dataset provided by the leading online job platform in India, which held a dominating market share of over 70 percent in 2017. The platform hosts job ads for firms and charges approximately INR 1000 (USD 15) for posting a job ad. Job seekers are able to register, search and apply for jobs at no cost. After the application, subsequent recruitment and hiring processes are conducted by the firms advertising the vacancies. We observe information on number of vacancies for each posted job, job title, job role, job functional area, firm ID, date of posting, salary and educational and experience requirements along with a detailed job description. Most importantly, we observe the location of posted job (city within India, or country name if foreign-based role).

For our core analyses, we focus on 871 firms that posted at least one US-based job vacancy prior to June 2016 i.e., Trump's Primary win. The summary statistics for the jobs posted by these firms for locations based in India and the US are given in Appendix Table B.1. These 871 firms on average post 81 US-based jobs, and $6,276$ India-based jobs every month. Around 80% jobs posted in India and 88% jobs posted for the US are in the services sector.

We use the information provided in job role, industry, functional area, skills, title and job description of each job advertisement to map it into Standard Occupational Classification (SOC-2010) at the 6-digit level. To do this, we utilize sentence transformers and semantic similarity algorithms detailed in Bafna *et al.* (2023). These use state-of-the-art large language models to undertake this task. We also extract firm names from the job description text to match firms to other publicly available firm-level data. Appendix Section A.2 offers more detailed information on data, data cleaning methods, and comparisons with the Periodic Labor Force Survey, a nationally representative employment data at individual level for India.

The key advantage of the job postings data vis-a-vis the administrative data is its high frequency and detailed occupational classification. In 2018, more than 5.7 million vacancies across 1.2 million postings from 51,490 unique firms were posted on the platform, compared to 10.4 formal jobs in the 2017-18 Periodic Labour Force Survey in urban India. Thus, the number of formal job vacancies in a year to total formal employment in India is around 0.1. This is similar to estimates using postings data from the Burning Glass of roughly 0.08 vacancies per employed individual for the US (Acemoglu *et al.*, 2022). Moreover, these are the only data where we can observe demand for workers by a given firm for both India and overseas based postings.

4 Shift in Postings for US-based Jobs

We begin by examining the change in growth of aggregate US based job postings in Figure 1, Panel (b). The initial year 2014 is normalized to 100. The first green vertical line corresponds to Trump's Primary win in June 2016 and the second black vertical line signifies the RFE escalation in April 2017. A noticeable decline in aggregate job postings is observed starting from June 2016, which persists until 2019. However, this decline in job postings could be due to changing firm composition or other factors. To rule out this possibility, we utilize firm-level panel data and examine the changes in postings for US-based jobs using the following specification:

$$y_{fmt} = \sum_{k=H1-2015}^{H1-2019} \alpha_k \mathbf{1}[Period^k_{mt}] + \delta_{fm} + \varepsilon_{fmt} \tag{1}$$

where, y_{fmt} is the log count of US based postings by firm f in month m and year t.[8] k varies from the first half ($H1$) of 2015 to the first half of 2019, while year 2014 serves as the baseline.[9] The coefficients α_k depict the dynamic evolution of postings after controlling for firm specific time-invariant unobserved heterogeneity as well as any seasonality in their hiring trends δ_{fm}. This specification also allows us to directly check for any pre-trends in the evolution of postings before the two event dates that increased uncertainty around the visa policy. Standard errors are clustered at firm level.

These estimates are reported in Figure 1, Panel (c). We find that coefficients α_k are insignificant until June 2016, and become significantly negative thereafter. This indicates that the uncertainty around potential immigration restrictions increased after Trump's Primary win in June 2016, led to a decline in advertising of US-based jobs in India. After the primary win, the point estimates are around -0.15 signifying a 15 percent decline in postings. Further, after the increase in RFE, postings decline by an average 22 percent. We conduct a similar exercise using vacancies as the dependent variable and find similar results (Appendix Figure B.2). We report additional robustness of these results at occupation level, and using IHS transformation of dependent variables, in Appendix Section A.3.

5 Impact on India-based Job Postings

We focus on the consequences of the increased uncertainty surrounding hiring H-1B immigrants for US-based roles on job listings for India-based positions. Several potential factors can influence this. First, if firms are uncertain about employing Indian immigrants and cannot find substitute employees in the US, they may offshore these US-based jobs to India. Second, firms might offset their business losses in the US, as they are unable to hire desired candidates,

[8] We add 0.01 for firms that have zero job ads posted in a given month-year before taking the log transformation. We also estimate the specifications using inverse hyperbolic sine (IHS) transformation (Bellemare & Wichman, 2020) of zero values instead and find similar results. We also estimate the effects on levels of postings and vacancies and find similar results.

[9] We divide the year into two half years so that one can see changes over time after Trump won the Republican Primary election in June 2016. January to June of a year is the first half year ($H1$) and July to December is the second half year ($H2$) for the year t.

by expanding their operations in India. Lastly, firms may hire US workers for the roles previously filled by H-1B visa holders. The first and second channels would increase overall job postings in India, while the third channel would decrease them. The net effect on job listings in India is therefore ambiguous.

5.1 Empirical Strategy

We assess the impact on firms that were exposed to this shock, specifically firms that had posted at least one job ad for US-based roles prior to June 2016. We hypothesize that firms more reliant on H-1B visas would be more affected by this uncertainty and are more likely to change their hiring decisions in India. To encapsulate this, we define firm-level treatment or exposure as the percentage share of US-related job postings out of all job postings in the pre-shock period by the firm. Using the data from the pre-shock period (January 2014-June 2016), we define the treatment for firm f as:

$$Share_f = \frac{\text{US Postings}_f}{\text{Total Postings}_f} \times 100. \tag{2}$$

The method of constructing treatment intensity in this manner is similar to Clemens *et al.* (2018).[10] Using $Share_f$, we estimate the firm-level impact on India-based job postings:

$$y_{fmt} = \mu_1(\mathbf{1}[Primary]_{mt} \times Share_f) + \mu_2(\mathbf{1}[RFE]_{mt} \times Share_f) + \delta_{fm} + \delta_{mt} + \varepsilon_{fmt} \tag{3}$$

where y_{fmt} is the log count of India-based postings by firm f in month m and year t, $\mathbf{1}[Primary]$ and $\mathbf{1}[RFE]$ are the indicator variables for July 2016-March 2017, i.e., between the primary win for Trump and the RFE escalation, and after April 2017 when the RFE increased, respectively. δ_{fm} are firm-month fixed-effects that capture unobserved variation at firm level and also account for any firm-level monthly seasonality in postings. δ_{mt} are time

[10] Clemens *et al.* (2018) use fraction of seasonal agricultural labor in a state constituted by Braceros at the program's peak as the treatment intensity towards the program for that state.

fixed effects at month-year level, which capture any time-varying variation common to all firms. Standard errors are clustered at firm level. The coefficients of interest are μ_1 and μ_2. Assuming that trends in the outcome would have been similar in the firms most affected by H-1B uncertainty and the less affected firms, the estimates μ_1 and μ_2 capture the effect of firms' exposure to this shock on demand for India-based jobs.

5.2 Pre-trends and Dynamic Effects of H-1B Uncertainty

A potential concern with our estimation strategy could be that our results are driven by systematic growth rate differences across firms of different size, internationalization, or other firm characteristics, that could be correlated with firms' share of US-based postings. To address this, we plot event study estimates that allow us to examine pre-trends in postings and vacancies for India-based jobs, and to estimate dynamic effects over time using the below specification:

$$y_{fmt} = \sum_{k=H1-2015}^{H1-2019} \beta_k(\mathbf{1}[Period_{mt}^k] \times Share_f) + \delta_{fm} + \delta_{mt} + \varepsilon_{fmt} \tag{4}$$

where y_{fmt} is the log count of India-based postings by firm f in month m and year t, as before k varies from the first half of 2015 to the first half of 2019 with year 2014 as the baseline. The coefficients β_k from first half year of 2015 ($H1-2015$) to the first half year of 2019 ($H1-2019$) show the dynamic effect of firms' exposure to this shock on demand for India-based jobs. We can directly check for any pre-trends in the effects before the two event dates that increased uncertainty around the visa policy. Standard errors are clustered at firm level.

Figure 2 plots the coefficients on $Share_f$ for each half-year, using 2014 as the base period. Panel (a) shows the results for job postings. Prior to Trump's Primary win, we observe no discernible pre-trends in India-based job postings for firms more reliant on H-1B visas. After Trump's Primary win, there is a significant surge in India-based job postings by these firms.

This upward trend continues, particularly after the escalation in RFE from mid-2017, and it remains persistent until June 2019. The impact on posted vacancies in Panel (b) follows a similar trajectory. These results underscore a sustained increase in hiring for India-based positions, with firms more affected by the shock leading the shift.[11]

5.3 Firm Response to H-1B Uncertainty

Having shown that the critical identifying assumption of parallel pre-trends holds, we next show the results from estimating equation 3. The results in Table 1 show a significantly positive impact of this shock on India-based postings and vacancies by firms. Firms with higher $Share_f$, indicating greater exposure to the shock, increase their postings for India-based jobs (Column (1)). Notably, this increase begins in the period from July 2016–March 2017, with the postings increasing by 10 percent for a 10 percentage point increase in $Share_f$. The impact is slightly more pronounced after the RFE escalation, with a 10 percent increase in $Share_f$ leading to a 17 (0.017*10) percent increase in postings. These findings align with the timing of the decline in postings for US-based jobs, which began in the second half of 2016 following Trump's Primary win. Thus, the heightened uncertainty surrounding the H-1B program, spurred by the increased likelihood of Trump winning the Presidential elections, led to changes in firms' hiring decisions for India-based roles.

To account for potential trends in outcome variables at the firm level, we further control for firm-month-year linear trends in column (2). We continue to observe a 7.6 and 11.8 percent increase in India-based postings for the two sub-periods for every 10 percentage point increase in treatment intensity. The results remain consistent with quadratic time trends (results omitted for brevity). Finally, columns (3)-(4) report the estimates with vacancies as the dependent variable, and we find similar results. The findings remain robust to inverse hyperbolic sine (IHS) transformation of the dependent variables, using a binary indicator

[11] We further scrutinize these results using a binary indicator for treatment, in Appendix Figure B.3 respectively. We continue to find no pre-trends and similar dynamic effects. We also check the robustness of these estimates to IHS transformation and levels of the dependent variables and our findings remain consistent. These results are available on request.

for the treatment variable, and considering the absolute number of postings and vacancies (instead of log). Further details on these checks are provided in Appendix Section A.4.

6 Mechanisms

6.1 Which Occupations Witness Increase in India-based Jobs?

In section 5.3 we show that the uncertainty surrounding the ability of firms to hire under the H-1B visa program increases postings for jobs based in India. Such a rise could be attributed to offshoring of jobs from the US to India or expansion of India operations to make up for potential losses in US based business. If offshorability is indeed a crucial factor, we should expect heterogeneity in the increase in postings for India-based jobs across different occupations, based on their potential to be offshored.

We evaluate this hypothesis by estimating the heterogeneous effects of the treatment on India-based postings by an index for offshorability of an occupation. To do this, we use the standardized measure for offshorability index at SOC-6 digit level by Blinder *et al.* (2009) (details in Appendix Section A.5). For ease of exposition, we use a single indicator *Post* for denoting the period after the Trump won the Primary election in June 2016, instead of estimating coefficients over the sub-periods.

We report the results in Table 2. Panels A and B report the impact on firm-level postings and vacancies, respectively. The triple interaction terms in all specifications are positive and significant. In the most stringent specifications (columns 3-4), we compare occupations within a firm that vary based on their offshorability by including firm-year-month fixed effects. In terms of magnitude, a one-standard-deviation increase in offshorability of an occupation for a mean firm with a 20 percentage point share of US based postings leads to a 2 percent ($0.0010 \times 20 \times 100$) increase in job postings in India. Thus, for occupations that have the highest and the lowest offshorability index value, a mean firm increases relative postings by 6 percent ($0.0010 \times 20 \times 100 \times 3$). We find a similar impact on vacancies in Panel B.

Further, Appendix Figure B.4 shows no differential change in postings based on occupation offshorability before the Primary win by Trump. However, there is a clear increase thereafter. Taken together, these results show that uncertainty surrounding H-1B policy prompts firms to increase hiring in India for roles that can be offshored.

To check the robustness of these results, we estimate Equation 3 for various occupation groups and report the results in Appendix Table B.7. Occupations that are easier to offshore, like computer related jobs, managers (these are largely managers in the domain of computing), engineers (these include software and other engineers), financial sector jobs and animation are grouped in columns (1)–(5). Those in columns (8)–(10) are more difficult to offshore like healthcare and community workers or those conducting teaching and research at universities. The results indicate a significant increase in India-based postings for occupations more amenable to offshoring, while there's an insignificant change for occupations that are less offshorable. A similar pattern emerges for vacancies in Panel B.

We also use two alternate measures on work-from-home and physical proximity created by Mongey *et al.* (2021) to capture occupation offshorability. We find that firms increase postings and vacancies for India-based jobs for occupations with a higher likelihood of work-from-home or those requiring lower physical proximity, in response to the shock (Appendix Table B.8).

6.2 Which Firms Relocate jobs?

Next, we check whether firms headquartered in India or in the US are more likely to relocate jobs to India. To test this, we manually extract firm names from job descriptions and identify their headquarter location. We are able to match 640 firms out of 871 for this analysis. Of these, 282 are headquartered in India, 270 in the US and 56 in other countries.[12] Table 3, columns (1)-(2), report the results for postings. Interestingly, firms with Indian headquarters show a larger increase in postings, with a 10 percentage point increase in $Share_f$ leading

[12] Of the 270 headquartered in the US, 200 currently have an Indian subsidiary. However, these firms could have established their Indian offices post-2016. We are unable to determine the headquarter location country for 32 firms.

to a 22.2 percent increase in these firms' India-based postings after the shock (column 1). The same shock increases postings by only 11.2 for the US headquartered firms, as the triple interaction term is negative. Once we control for firm-specific trends in column (2), the increase for the US headquartered firms becomes insignificant, while it remains positive and significant at 12 percent for India headquartered firms. We find similar effects for vacancies. We also report event study plots for these specifications in Appendix Figure B.5. These findings suggest that firms with Indian headquarters are more likely to relocate jobs to India amidst H-1B visa policy uncertainty.

In Section 6.1 we showed that occupations that have higher offshoring potential register more posting of India-based jobs, thereby indicating offshoring of jobs from the US to India. To further investigate whether India-based firms were expanding Indian operations to compensate for US losses or offshoring jobs from the US to India, we match firm names in job postings data to the Prowess database maintained by the Centre for Monitoring Indian Economy (CMIE), which provides financial information for over 40,000 listed and unlisted Indian firms (Prowess Data). We are able to match 73 firms using an exact name match. To be consistent with our earlier analyses, we use information from Indian financial year 2014-15 (April 2014–March 2015) to 2019-20.[13]

We estimate the impact on various financial outcomes of these firms in response to the shock. If firms increase Indian operations, their domestic sales would go up, else if jobs are offshored their exports would go up. Appendix Table B.9 reports these results. We find that exports increase by 5.6 percent as the share of US based postings of a firm increases by 10 percentage points after the uncertainty in visa policy begins. Appendix Figure B.6 reports the estimates from an event study specification for exports. We see no pre-trends before 2016 and the exports rise immediately after Trump's win in the primary. At the same time, there

[13]The year 2013 also saw a large discussion in the US policy making space on the H-1B visa policy. For instance, there was a proposal in the Senate to increase the cap under the program from 65,000 to 110,000 (Brookings Report). It also proposed other changes to ease the hiring of workers under the program. The recommendations, however, were not eventually enforced but created a stir in the industry due to differential future possibilities of hiring under the program that could have affected firms' perception about hiring.

is no effect on domestic sales or profits.

Next, we test if expansion in Europe could potentially explain the above results on increased firm exports. The US is followed by Europe in terms of service exports from India. If a firm's US business operations suffer due to the shock, it could try to compensate by expanding its European operations which should be reflected in increased postings for Europe-based jobs. In Appendix Table B.10, columns (1) and (2), report the results and find no impact on Europe-based postings.

6.3 Spillover Effects

Next, we examine the spillover effect on firms that are not directly exposed to the US market via the H-1B visa policy, but might be indirectly affected by this shock in India. For instance, US-based firms uncertain about hiring Indian workers under the H-1B may choose to offshore jobs to other firms in the Indian market. Consequently, Indian firms that specialize in occupations impacted by this shock could increase their hiring to cater to the new demand created by offshoring. To assess this, we calculate the occupational exposure to this policy shock by calculating the pre-shock share of postings in H-1B dependent occupations out of the total postings by a firm at a 6-digit SOC level.

In columns (3) and (4) of Appendix Table B.10, we note an increase in postings by India-based firms, which had never posted a US-based vacancy, but specialize in occupations reliant on H-1B visa, after Trump's Primary win. The coefficient on the interaction term is positive and significant for both specifications, indicating that a 10 percentage point increase in firms' posting jobs in these specialized occupations leads to a 2.6 percent increase in job postings by these firms. This suggests that there is a positive spillover effect on other firms in the Indian market that are not directly exposed to this shock, probably on account of increased outsourcing from US to India.

7 Conclusion

The effect of policy uncertainty around migration on firm's decision making on employment has received little attention in the literature. Exploiting the uncertainty around ability of firms to hire under the H-1B visa, without any direct changes in the visa caps, we observe that firms with a higher dependency on the H-1B program increase their job listings in India while curtailing US-based vacancies for Indians. Intriguingly, this shift emerges immediately post Trump's primary victory, underscoring the weight of policy uncertainty on firms' hiring decisions. Our results suggest offshoring of jobs from the US to India, rather than an increase in India based operations by these firms. Our findings also underscore that protectionist measures, instead of promoting domestic benefits, might prove counterproductive given agility in firms' decision-making.

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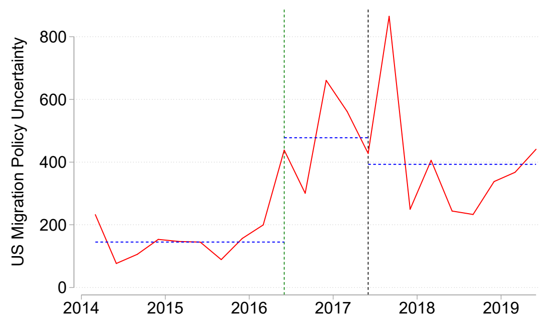
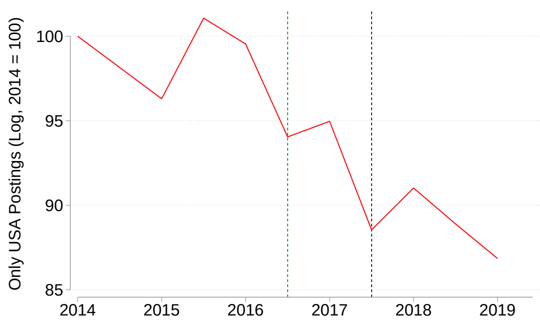
Figure 1: Evolution: H-1B Visa Uncertainty and US-based Openings in India

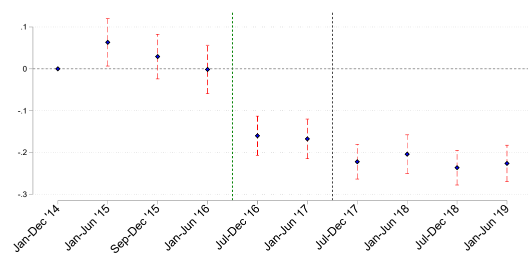
(a) EPU Migration Index



(b) Postings for US-based Jobs



(c) Event Study: Postings for US-based Jobs

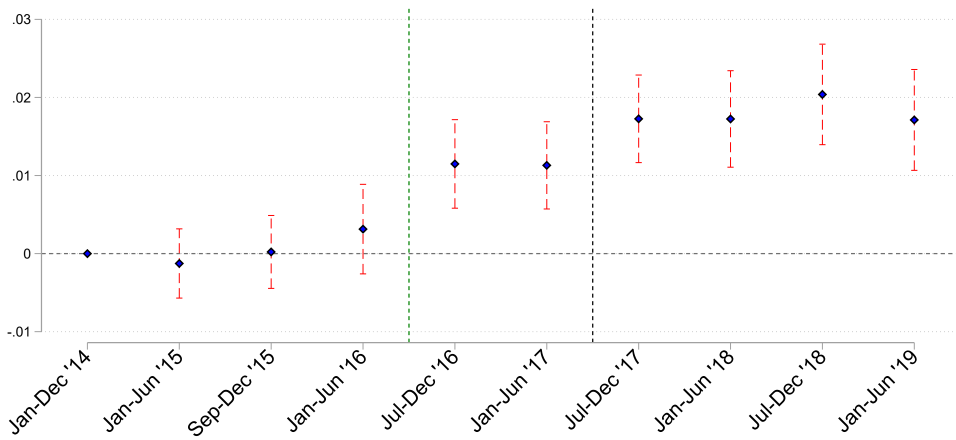


Notes: Panel (a) plots quarterly Economic Policy Uncertainty Index for Migration for the United States of America. The blue dotted lines represent the means for various periods: 144.95 in the pre-period January 2014 to March 2016, 477.72 during the period April 2016 to June 2017, and 392.93 in the period July 2017 to June 2019. It is constructed by searching for related terms under 4 heads - Migration, Economy, Policy, Uncertainty. Articles with at least one term from each of four heads among the US newspapers indexed by the Access World News Newsbank database for the United States are then counted. Each index is normalized to a mean value of 100 from 1995 to 2011. For further methodological details about the construction of the index see EPU Website. Panel (b) plots the log number of postings for the United States based jobs at a half-yearly frequency, with the log of postings in the first six months of 2014 as the base. Panel (c) shows the estimates (α_k) on each half year, with the first year 2014 as the base, corresponding to equation 1. The coefficients show the change in firm-level US based postings over time. In both panels (b) and (c), we only keep the job ads where only cities based in the United States are mentioned. For instance, if a job ad contains both a city in India (or any other country apart from the US) and in the US, then such ads are not considered. The first vertical line corresponds to Trump's win in the Republican primary in June 2016. The second vertical line corresponds to RFE escalation in April 2017. The standard errors are clustered at firm level and 95% confidence intervals are plotted in Panel (c).

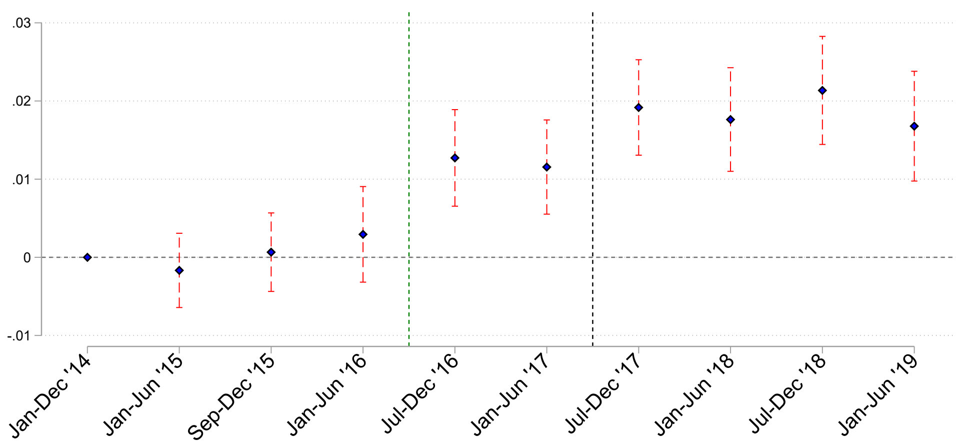
Source: EPU for panel (a). Data from all job ads posted on the portal during January 2014-June 2019 for panel (b) and panel (c).

Figure 2: Effect of Visa Regime on India-based Postings

(a) Postings



(b) Vacancies



Notes: The plots show the β_k estimates for equation 4. The dependent variable is log of India based postings and vacancies in a given firm-month-year in panels (a) and (b), respectively. To deal with zero values of the postings we add a small value of 0.01 before taking the log transformation. These estimates capture the impact on firm-level postings in panel (a) and vacancies in panel (b) in India as a function of its exposure to the shock for each half year in the data. We keep firms that had at least one US based posting during the pre-shock period. All specifications include firm-month and year-month fixed effects. The first dashed vertical line corresponds to Trump's win in the primaries in June 2016, while the second dashed vertical line corresponds to the RFE escalation in April 2017. The standard errors are clustered at firm level and 95% confidence intervals are plotted.

Source: Data from all job ads posted on the portal during January 2014-June 2019.

Table 1: Effect of Visa Regime on India-based Postings

	(1)	(2)	(3)	(4)
	Postings		Vacancies	
Primary × $Share_f$	0.0103***	0.0076***	0.0110***	0.0087***
	(0.0021)	(0.0023)	(0.0022)	(0.0025)
RFE × $Share_f$	0.0169***	0.0118***	0.0176***	0.0134***
	(0.0022)	(0.0031)	(0.0024)	(0.0033)
Observations	49764	49764	49764	49764
R-Squared	0.640	0.729	0.633	0.722
Mean	8.3237	8.3237	15.8539	15.8539
Firm-Month FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Firm-Month-Year Trends	No	Yes	No	Yes

Notes: The table shows the estimates for equation 3. The dependent variable is log of India based postings and vacancies in a given firm-month-year in columns (1)-(2) and (3)-(4), respectively. To deal with zero values of the postings and vacancies we add a small value of 0.01 before taking the log transformation. Primary is an indicator variable equal to 1 for the period July 2016-March 2017 and 0 otherwise. RFE is an indicator variable equal to 1 for the period April 2017-June 2019 and zero otherwise. *Share* captures the share of US postings among all postings by a firm in the period before the policy change. We keep firms that had at least one US based posting during the pre-shock period. Mean refers to the mean of the dependent variable without log transformation. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in parentheses are clustered at firm level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Data from all job ads posted on the portal during January 2014-June 2019.

Table 2: Effect on India Postings: Heterogeneity by Occupation Offshorability

	(1)	(2)	(3)	(4)
Panel A: Postings				
Post × $Share_f$ × Offshoring	0.0010**	0.0009**	0.0010**	0.0010**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Post × $Share_f$	0.0038***	0.0039***		
	(0.0013)	(0.0013)		
Post × Offshoring	-0.0250***	-0.0253***	-0.0190***	-0.0188***
	(0.0066)	(0.0066)	(0.0054)	(0.0054)
Observations	1204979	1198352	1201677	1194983
R-Squared	0.365	0.498	0.439	0.568
Mean	0.3001	0.3001	0.3009	0.3009
Panel B: Vacancies				
Post × $Share_f$ × Offshoring	0.0010**	0.0009**	0.0010**	0.0009**
	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Post × $Share_f$	0.0039***	0.0040***		
	(0.0013)	(0.0013)		
Post × Offshoring	-0.0259***	-0.0261***	-0.0194***	-0.0192***
	(0.0069)	(0.0069)	(0.0058)	(0.0058)
Observations	1204979	1198352	1201677	1194983
R-Squared	0.366	0.499	0.439	0.568
Mean	0.5022	0.5022	0.5034	0.5034
Firm-SOC FE	Yes	No	Yes	No
Firm-Month FE	Yes	No	Yes	No
Firm-SOC-Month FE	No	Yes	No	Yes
Year-Month FE	Yes	Yes	No	No
Firm-Year-Month FE	No	No	Yes	Yes

Notes: The table shows the estimates for equation A.5. These capture the impact on India based postings of a firm by the pre-shock exposure of the firm to US based postings and the degree of offshorability of an occupation. The dependent variable is log of India based postings (Panel A) and vacancies (Panel B) in a given firm-occupation-month-year. The occupation is defined at SOC 2018-6 digit level using the machine learning algorithm by Bafna *et al.* (2023). To deal with zero values of the postings and vacancies we add a small value of 0.01 before taking the log transformation. Post is an indicator variable equal to 1 for the period July 2016-June 2019 and 0 otherwise. *Share* captures the share of US postings among all postings by a firm in the period before the policy change. *Offshore* is the standardized measure for offshorability index of occupation (Blinder *et al.*, 2009). We keep firms that had at least one US based posting during the pre-shock period. Mean refers to the mean of the dependent variable without log transformation. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in parentheses are clustered at firm level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Data from all job ads posted on the portal during January 2014-June 2019.

Table 3: Effect on India Postings: Heterogeneity by Headquarter Location

	(1)	(2)	(3)	(4)
	Postings		Vacancies	
Post × Share_f × USA HQ	-0.0113*	-0.0110*	-0.0121*	-0.0119*
	(0.0063)	(0.0063)	(0.0067)	(0.0066)
Post × Share_f	0.0222***	0.0121**	0.0233***	0.0138**
	(0.0062)	(0.0059)	(0.0066)	(0.0062)
Observations	34056	34056	34056	34056
R-Squared	0.632	0.721	0.625	0.713
Mean	10.0027	10.0027	19.0213	19.0213
Test: USA Effect==0	0.0000	0.6995	0.0001	0.5407
Firm-Month FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Firm-Month-Year Trends	No	Yes	No	Yes

Notes: The table shows the heterogeneous impact on India based postings of a firm based on the pre-shock exposure of the firm to US based postings, by the headquarter location of the firm. The dependent variable is log of India based postings and vacancies in a given firm-month-year in columns (1)-(2) and (3)-(4), respectively. To deal with zero values of the postings and vacancies we add a small value of 0.01 before taking the log transformation. We use the specification in equation 3 and estimate the heterogeneity of the main impact by firm headquarter location. For simplicity, we combine the *Primary* and *RFE* time periods into one variable called *Post* – an indicator variable equal to 1 for period July 2016-June 2019 and 0 otherwise. *Share* captures the share of US postings among all postings by a firm in the period before the policy change. *USA HQ* takes a value of one for firms having headquarter location in the USA and zero otherwise. We keep firms that had at least one US based posting during the pre-shock period. Mean refers to the mean of the dependent variable without log transformation. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in parentheses are clustered at firm level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Data from all job ads posted on the portal during January 2014-June 2019.

A Appendix

A.1 H-1B Visa: Additional Institutional Details

Foreign high-skilled workers can be hired through a variety of visa programs in the US. These include, for example, the H-1B, L-1, O, OPT, and TN visas.[1] Of all these, the H-1B program remains the largest, accounting for almost 50% of the various temporary work visas. It is a non-immigrant visa initially granted for 3 years and is extendable to 6 years. It is only available for applicants that have at least a US equivalent bachelor's degree. Additionally, the role must be in a specialty occupation.[2] Occupations that qualify for the H-1B visa are typically in fields such as technology, finance, engineering, architecture. Thus, H-1B program caters to extremely high skilled immigration.

To apply for H-1B visa, the employer needs to first submit a Labour Condition Application (LCA) to the Department of Labor's Employment and Training Administration (DOLETA). This details the position employees will be hired for, their wages, and location. The submission costs are non-trivial - in 2016 the filing fee was between $1,700-$6,500. Thus, only firms which are serious about hiring workers under the program are likely to apply. Conditional on the LCA approval, the firm files an I-129 petition with the USCIS, following which the ultimate decision about the visa application is made. The allotment of visas is then done by a lottery across all the valid H-1B applications. The H-1B visa cap is limited to 65,000 visas per year. All the H-1B applicants are pooled and of these 65,000 are randomly selected and granted visas.[3] After this, applicants with the US Master's degrees who are not selected in the lottery are further randomly allotted 20,000 visas.

[1] L-1 visa is generally used for within-company transfers.

[2] Specialty occupations under the USCIS regulations, must either require a bachelor's or higher degree or its equivalent that is normally the minimum entry requirement for the position or the position is so complex or unique that it can be performed only by an individual with the degree.

[3] This cap has been changing over the years. For instance, during the 1990's the cap was 65,000, it increased to 1,95,00 during 1998-2000, the cap thereafter reverted to the initial level of 65,000 visas, with 20,000 additional visas granted to applicants with a graduate degree from 2006 onwards. Thus, since 2006, the cap has remained at 85,000. Notably, the cap only applies to new H-1B visas issued to private sector businesses while non-profit institutions including universities are not restricted.

The H-1B petitions are accepted until the H-1B cap (85,000) is reached. Hence, the last date can vary based on the H-1B visa demand. For the fiscal years 2014-2019 the cap reached within the first 5-7 days of petitions opening (RedBus), hence, lotteries were used for allocation of visas. If a petition is successful, then the next step depends on whether you are currently residing in the United States or not. If the applicant is within the United States on a different visa category, they can start working after the H-1B status is updated and active. Candidates outside the United States, need to apply for consular processing at the US embassy in their country. Successful applicants can begin work from the next fiscal year i.e., October onwards. Indians form the largest pool of the H-1B visa workers - almost 70% (Mint, US State Govt Annual Report).[4]

A.2 Data Details

As discussed in the main paper, we have information on number of vacancies for each posted job, job title, job role, job functional area, location (city within India, else country name with or without city), company ID, date of posting, salary and educational and experience requirements along with a detailed job description. We first extract the country of location of the job ad wherever city name is provided. Below we first compare the India based jobs ads with nationally representative employment data in India. We then compare the job ads posted in India vs the US.

Appendix Table B.2 shows the summary statistics for all jobs by country of location. Column (1) shows for all postings, while column (2) shows for postings based in India while column (3) shows for postings based in the US. We briefly compare the jobs posted for India with the nationally representative Periodic Labor Force Survey (PLFS) data of 2017-18. The

[4]More visas are issued than the cap each year when people renew their existing H-1Bs or cap-exempt organizations apply for more visas. 6,800 out of the regular quota are also reserved for citizens of Chile and Singapore as part of a specific Free Trade Agreement. Around a third of all the granted visas in 2014 went to the top 13 outsourcing firms. The top recipients among these were Tata Consultancy Services, Infosys and Wipro, all with headquarters based in India. Other US based firms like Microsoft, Intel, IBM, Cognizant and Amazon were also big recipients. These firms typically contract with organizations in other sectors to handle various computing tasks (NYT).

posted jobs on the platform are located in urban India since urban towns and cities constitute the employment locations. Also, these jobs offer a regular salary and have a wage contract making them largely reflective of formal employment in the country. Hence, we restrict our comparison to urban workers who are salaried and have a formal wage contract in the PLFS data. Appendix Table B.2 shows that the jobs on the platform primarily are in the services sector (78% job postings) followed by manufacturing (15.7% job postings) and construction (5.7% job postings). Even among the urban salaried wage workers with a formal contract, services sector jobs account for almost 70% employment, manufacturing accounts for 26% and the remaining proportion by the construction sector. Thus, the sectoral composition is very similar across both the platform and the formal employment data.

Almost all job ads on the platform post an annual salary range. The platform has this as a mandatory field but provides an option to the employers to hide the salary.[5] We take the mid of the salary range for a job ad as the relevant salary associated with it. The average annual salary for the job ads posted across all years is INR 0.7 million. Specifically, in 2017 for India as a location it was INR 0.68 million. In comparison, the average annual salary for a regular wage worker with a formal contract is INR 0.324 million in the PLFS 2017-18. The higher salary on the platform is also reflected in the higher required education. Almost 95% jobs require the candidate to be at least a graduate. In contrast, among regular wage workers with a formal contract, those have at least a graduate degree is 62% in the PLFS. Among the occupation categories, 65% of the salaried formal contract workers in the PLFS are employed in high skilled occupations (SOC's 1-4). Among the job ads this proportion stands at 81%. Therefore, the ads posted on the portal are for relatively higher skill jobs even within the salaried formal labor market in India. Given that we are interested in the labor market impacts of H-1B visa uncertainty, which affects only the higher skilled labor market, the job ads data is a good measure for this.

[5]This is because they provide preferred salary as a filter for candidates while searching on their platform.

A.3 Robustness: Impact on Posting for US-based Job Roles

We also investigate the changes in US based openings by aggregate sub-periods - Primary (June 2016-March 2017) and RFE (April 2017-June 2019) with January 2014-May 2016 as the base period. The estimates in column (1) and (2) of Appendix Table B.3 give the percentage change in firm-level postings and vacancies, respectively, in the two sub-periods. The results align with the event study discussed earlier. We conduct a similar exercise at an alternate degree of aggregation, 6-digit SOC occupation level. In each of these regressions, we control for SOC-month fixed-effects which filter out any unobserved monthly variation at the occupation level in US-based postings and vacancies. These estimates are reported in columns (3) and (4) and yield similar results as firm level regressions. We verify robustness with IHS transformation of dependent variables, instead of using log value of job postings and vacancies and find consistent results (Appendix Table B.4).

A.4 Robustness: Impact on Postings for Inda-Based Job Roles

Columns (1) and (2) in Appendix Table B.5 present the results using the inverse hyperbolic sine (IHS) transformation for the dependent variables. We continue to observe a significant increase in India-based postings and vacancies by firms more exposed to the shock. In columns (3) and (4), we employ a binary indicator to measure the exposure intensity of a firm to the shock. This indicator takes a value of one for firms that have above median share of US-based postings ($Share_f$), and zero otherwise. We continue to find that the firms more reliant on H-1B visas increased India-based jobs postings and vacancies after Trump's primary, a trend that persists until 2019. We further verify the robustness of our results by using levels of postings/vacancies as the dependent variable in columns (1)-(4) of Appendix Table B.6, and we continue to find similar results. Lastly, columns (5)-(6) check whether the shock prompts firms to begin posting India-based roles. We consider an indicator variable that takes a value of one if a firm posted an India based vacancy in a given month, else zero. We find a positive increase (2.2 percent for a 10 percentage point increase in $Share_f$) in the probability of posting an ad for India-based roles by firms following the shock. This suggests that firms without affiliate offices in India may have started India-based operations, or firms with small India-based teams may have expanded them in response to the shock.

A.5 Offshoring

We construct a panel data at firm-occupation level to test the offshoring channel. We then estimate the heterogeneous effects on India based postings by an index for offshorability of an occupation:

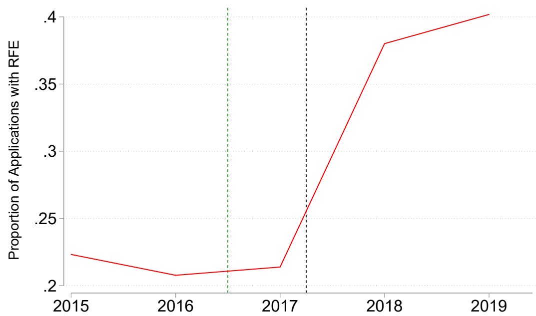
$$
\begin{aligned}
y_{fjmt} = \alpha + \omega_1(\mathbf{1}[Post]_{my} \times Share_f \times Offshore_j) + \omega_2(\mathbf{1}[Post]_{mt} \times Share_f) \\
+ \omega_3(\mathbf{1}[Post]_{mt} \times Offshore_j) + \delta_{fjm} + \delta_{fmt} + \epsilon_{fjmt} \quad \text{(A.5)}
\end{aligned}
$$

where the dependent variable is the logarithm of number of postings (or vacancies) for occupation j posted by firm f in month m year t. Here, *Post* is an indicator variable that takes a value of one for time period after Trump wins the primary till June 2019. $Offshore_j$ is the standardized measure for offshorability index of occupation at SOC 2018-6 digit level by Blinder *et al.* (2009). The mean of the standardized index for the occupations in our analyses is 0.33, indicating that the occupations posted by the firms in our sample are on average more offshorable than all occupations (Appendix Table B.1). The original index ranges from 0 to 100, with 0 representing the lowest offshorability potential and 100 the highest. The mean of the raw index (range: 0-100) from Blinder *et al.* (2009) is 31.9. We standardize the index for ease of interpretation.

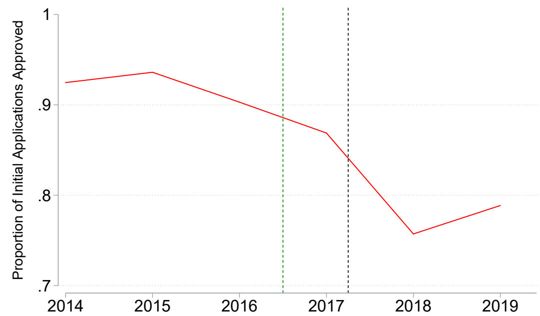
B Appendix: Additional Figures and Tables

Figure B.1: Trends in H-1B Applications

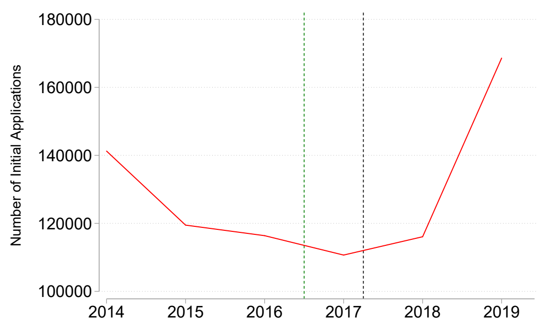
(a) Proportion of Applications with RFE



(b) Proportion of Applications Approved



(c) H-1B Applications

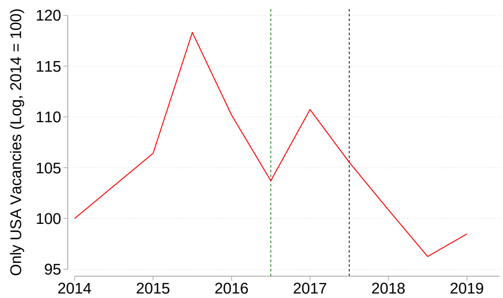


Notes: Panel (a) plots the proportion of H-1B applications that were received a request for further evidence (RFE) in a given fiscal year (the data for which is only available from 2015 for every year). For instance, year 2016 refers to applications received from October 2015-September 2016. Panel (b) plots the proportion of H-1B applications approved for that fiscal year. Panel (c) plots yearly trends in number of new H-1B visa applications received by the USCIS in a given US fiscal year. The first vertical line corresponds to Trump's win in the Republican primary in 2016. The second vertical line corresponds to the RFE escalation in 2017.

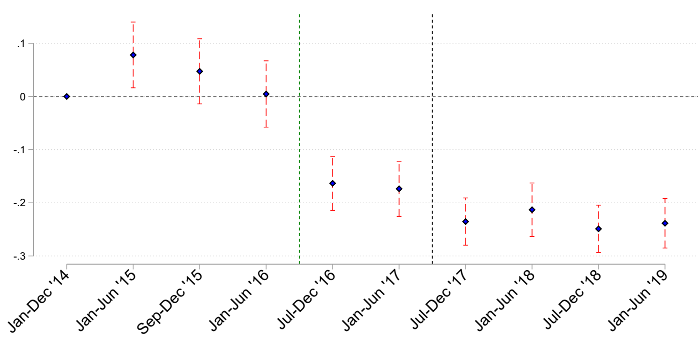
Source: For H-1B applications and approvals (USCIS). For Requests for Evidence (USCIS).

Figure B.2: US-based Vacancies in India

(a) Evolution: Aggregate Postings for US-based Jobs

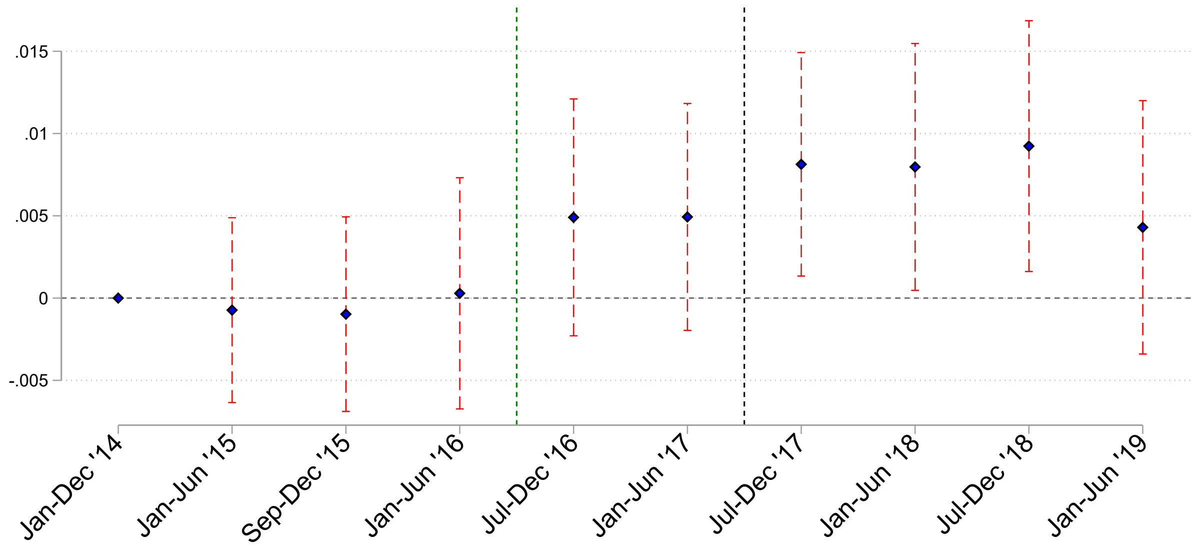


(b) Event Study: Vacancies for US-based Jobs



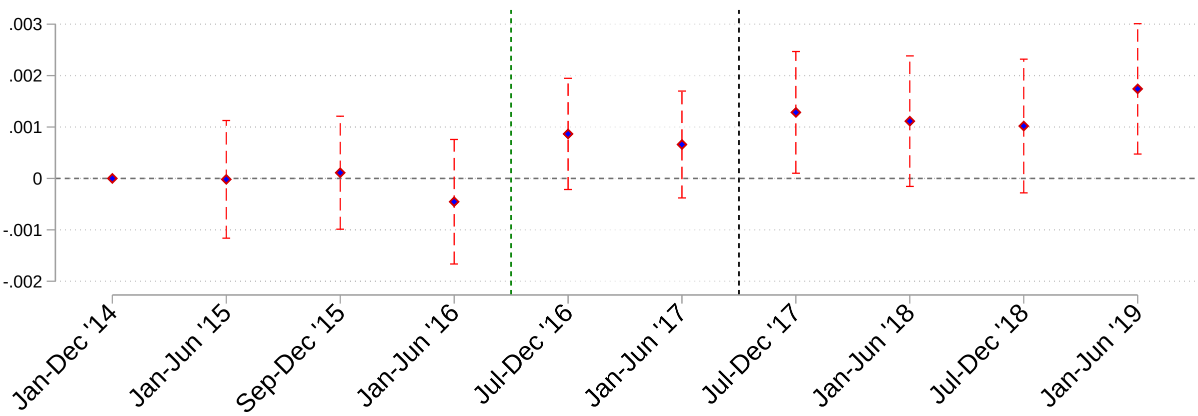
Notes: Panel (a) plots the log number of vacancies for the United States based jobs at a half-yearly frequency, with the log of vacancies in the first six months of 2014 as the base. Panel (b) shows the estimates (α_k) on each half year, with the first year as the base, corresponding to equation 1. To deal with zero values of the postings we add a small value of 0.01 before taking the log transformation. The coefficients show the change in firm-level US based vacancies over time. In both panels, we only keep the job ads where only cities based in the United States are mentioned. For instance, if a job ad contains both a city in India (or any other country apart from the US) and in the US, then such ads are not considered. The first vertical line corresponds to Trump's win in the Republican primary in June 2016. The second vertical line corresponds to the RFE escalation in April 2017.

Figure B.3: Effect of Visa Regime on India-based Postings: Robustness (Binary indicator)



Notes: Figures plot the β_k estimates from equation 4. The dependent variable is log of India based postings in a given firm-month-year. To deal with zero values of the postings we add a small value of 0.01 before taking the log transformation. These estimates capture the impact on firm-level India-based log postings as a function of its exposure to the shock in each half-year in the data. The specification uses a binary indicator to measure exposure to the shock with firms' having above median share of US postings in the pre-shock period defined as treated. We keep firms that had at least one US based posting during the pre-shock period. All specifications include firm-month and year-month fixed effects. The first dashed vertical line corresponds to Trump's win in the Republican Primary in June 2016, while the second dashed vertical line corresponds to the RFE escalation in April 2017. The standard errors are clustered at firm level and 95% confidence intervals are plotted. *Source:* Data from all job ads posted on the portal during January 2014-June 2019.

Figure B.4: Dynamic Effects on India-based Postings: By Occupation Offshorability

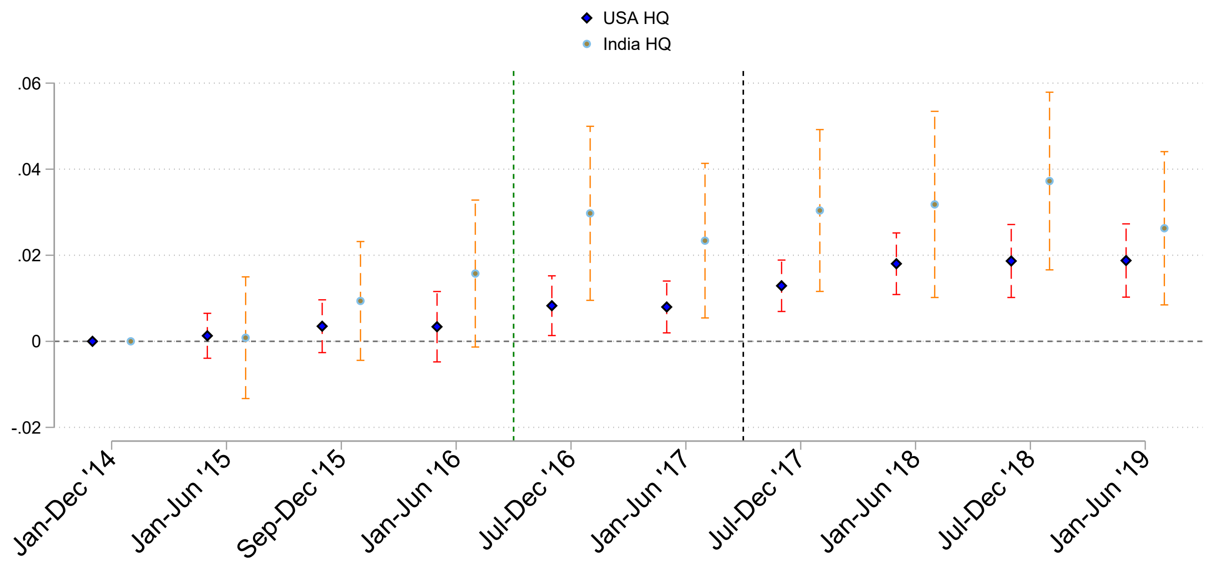


Notes: Figures plot the triple difference estimates (ω_k) for the impact on firm-level India-based postings in a given occupation as a function of its exposure to the shock, with heterogeneity across occupations based on their degree of offshorability. The estimating equation is:

$$y_{fjmt} = \sum_{k=H1-2015}^{H1-2019} \omega_k(\mathbf{1}[Period^k_{mt}] \times Share_f \times Offshore_j) + \sum_{k=H1-2015}^{H1-2019} \pi^1_k(\mathbf{1}[Period^k_{mt}] \times Share_f)$$
$$+ \sum_{k=H1-2015}^{H1-2019} \pi^2_k(\mathbf{1}[Period^k_{mt}] \times Offshore_j) + \delta_{fjm} + \delta_{mt} + \epsilon_{fjmt}$$

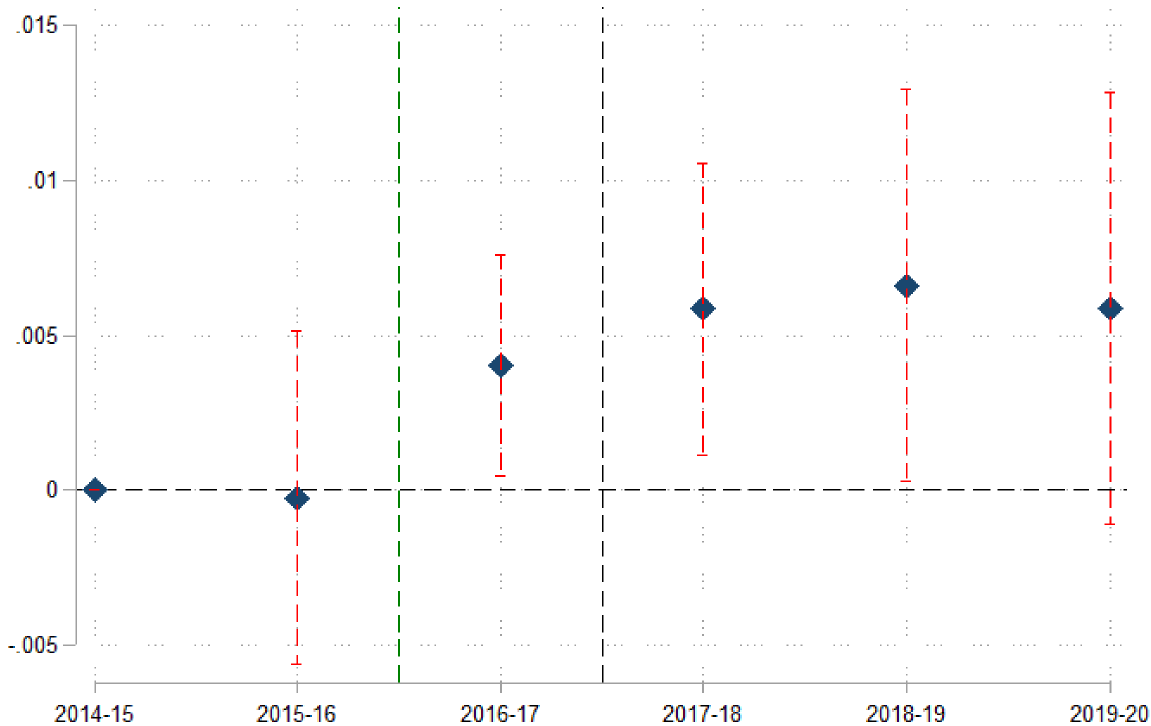
where y is the log of India-based postings by firm f in occupation j in month m in year t. To deal with zero values of the postings we add a small value of 0.01 before taking the log transformation. These estimates capture the impact on firm-level postings in India for a given as a function of its exposure to the shock and offshorability of the occupation for each half year in the data, with 2014 as the baseline year. The occupation is defined at SOC 2018 -6 digit level using a machine learning algorithm by Bafna *et al.* (2023). We use a standardized measure for offshorability index of occupation (Blinder *et al.*, 2009). The specification controls for firm-occupation specific unobserved effects and month level seasonality (δ_{fjm}) as well as month-year fixed effects (δ_{mt}). We keep firms that had at least one US based posting during the pre-shock period. The first dashed vertical line corresponds to Trump's win in the Republican Primary in June 2016, while the second dashed vertical line corresponds to the RFE escalation in April 2017. The standard errors are clustered at firm level and 95% confidence intervals are plotted.
Source: Data from all job ads posted on the portal during January 2014-June 2019.

Figure B.5: Dynamic Effects on India-based Postings: By Headquarter Location



Notes: Figures plot the β_k estimates from equation 4 separately for firms having US based headquarters and India based headquarters. The dependent variable is log of India based postings. To deal with zero values of the postings we add a small value of 0.01 before taking the log transformation. These estimates capture the impact on firm-level postings in India as a function of its exposure to the shock for each half year in the data with 2014 as the baseline year, by the location of the company's headquarters. We keep firms that had at least one US based posting during the pre-shock period. Further, sample here is restricted to companies with their headquarters in either US or India. All specifications include firm-month and year-month fixed effects.The first dashed vertical line corresponds to Trump's win in the primaries in June 2016, while the second dashed vertical line corresponds to the RFE escalation in April 2017. The standard errors are clustered at firm level and 95% confidence intervals are plotted.
Source: Data from all job ads posted on the portal during January 2014-June 2019.

Figure B.6: Effect of Visa Regime on Exports by Indian Firms



Notes: The figure plots σ_k estimates capturing the impact on firm-level exports in India as a function of firms' exposure to the shock using the below equation:

$$y_{ft} = \sum_{k=2015}^{2019} \sigma_k(\mathbf{1}[Year_k] \times Share_f) + \delta_f + \delta_t + \epsilon_{ft}$$

where is dependent is the log of exports of firm f in year t. We control for firm (δ_f) and year fixed-effects (δ_t). These estimates capture the impact on firm-level exports of India based firms as a function of their exposure to the shock for each year in the data with 2014 as the baseline year. We keep firms in Prowess which we could match by name with the job postings data. we then keep firms that had at least one US based posting during the pre-shock period. $Share_f$ is the share of US based postings for a firm in the preperiod using the data from job postings. It measures the exposure to the visa uncertainty shock for a firm. The first dashed vertical line corresponds to Trump's win in the Republican Primary in June 2016, while the second dashed vertical line corresponds to the RFE escalation in April 2017. The standard errors are clustered at firm level and 95% confidence intervals are plotted.

Source: CMIE Prowess 2014-2019 for firm level exports and job postings (January 2014-June 2016) for calculating the measure of exposure to the shocks for a firm.

Table B.1: Summary Statistics

	(1)	(2)	(3)	(4)	(5)
	Mean	SD	Min	Max	N
Panel A: US Postings					
Job Postings in a Month	80.8	53.2	16	215	66
Vacancies in a Month	251.1	198.2	21	842	66
Firms Posting in a Month	32.5	21.4	6	75	66
Job Postings by a Firm in a Month	0.093	1.043	0	50	57486
Vacancies by a Firm in a Month	0.288	3.918	0	100	57486
Panel B: India Postings					
Job Postings in a Month	6276.1	704.0	5013	7647	66
Vacancies in a Month	11953.8	1174.8	9340	14133	66
Firms Posting in a Month	416.4	50.0	347	489	66
Job Postings by a Firm in a Month	8.3	14.7	0	50	49764
Vacancies by a Firm in a Month	15.9	29.4	0	100	49764
Panel C: Treatment Variables					
Share of Only USA Postings (Firm-Level)	20.857	34.819	0.005	100.000	871
Offshoring Index (SOC-Level)	26.192	34.082	0.000	100.000	522
Standardized Offshoring Index (SOC-Level)	0.154	1.070	-0.668	2.471	522

Source: Panel A shows the summary statistics using data for US based postings. Panel B shows the summary statistics using data for India based postings, keeping data for firms which post at least one US based posting in the pre-shock period (January 2014-June 2016). For overall India and US based postings in a month, we use a panel created at monthly level using data from all job ads posted on the portal during January 2014-June 2019. For firm level India and US based postings in a month, we use a panel created at firm-month level using data from all job ads posted on the portal during January 2014-June 2019. In panel C. for showing the summary statistics for the share of only US based postings, we use a firm-level dataset containing firms with at least one only US based posting in the pre-shock period. We use the $Share_f$ (equation 2) calculated for these firms and report the summary statistics in the table. For the offshoring index, we use an occupation-level dataset keeping all occupations for which a posting is done in the data. We then assign it the offshorability potential given the occupational level offshoring index in Blinder *et al.* (2009). We also show the standardized value of this index which is used in the regressions for ease of interpretation.

Table B.2: Summary Statistics by Posting Location

	(1)	(2)	(3)
Variable	**Overall**	**Only India**	**Only US**
Postings Details			
Total Postings	6301079.0	5688142.0	6953.0
Total Vacancies	23577742.0	20325816.0	30193.0
Postings per Month	95470.9	86184.0	105.3
Vacancies per Month	357238.5	307966.9	457.5
Educational Distribution (Percent)			
Graduate	95.748	96.257	98.145
Post-Graduate	0.557	0.536	0.273
STEM Degree	20.448	20.352	27.326
Sectoral Distribution (Percent)			
Agriculture	0.573	0.548	0.360
Construction	5.671	4.463	3.164
Manufacturing	15.746	15.832	8.989
Services	78.010	79.156	87.487
Occupational Distribution (Percent)			
Management, Finance, and Business	37.878	37.992	22.927
STEM Related	39.347	40.058	67.930
Social Sciences and Arts	4.712	4.714	1.536
Technical Support Jobs	8.669	8.681	1.104
Construction and Production	1.752	1.115	0.970
Sales, Personal care and Food Services	7.438	7.295	5.430
Others	0.205	0.144	0.104
Experience Required			
0-2 Years	19.107	19.551	4.387
2-5 Years	40.656	41.155	23.803
5+ Years	40.237	39.294	71.811
Firms Posting			
Total Firms with Postings	142512.0	133150.0	1379.0
Firms Posting per Month	13376.1	12540.2	43.5
Annual salary			
Average Salary	697594.0	667155.9	5705653.8

Notes: Occupational Classification is done by assigning the 23 SOC major occupation groups to a broader category. Management, Business, and Finance include SOC codes 11 (Management Occupations) and 13 (Management Occupations). STEM Related include SOC codes 15 (Computer and Mathematical Occupations), 17 (Architecture and Engineering Occupations), 19 (Life, Physical, and Social Science Occupations), and 29 (Healthcare Practitioners and Technical Occupations). Social Services, Law, Education, and Arts include SOC codes 21 (Community and Social Service Occupations), 23 (Legal Occupations), 25 (Education, Training, and Library Occupations), and 27 (Arts, Design, Entertainment, Sports, and Media Occupations). Technical Support Jobs include SOC codes 31 (Healthcare Support Occupations), 33 (Protective Service Occupations), and 43 (Office and Administrative Support Occupations). Construction and Production include SOC codes 37 (Building and Grounds Cleaning and Maintenance Occupations), 47 (Construction and Extraction Occupations), 49 (Installation, Maintenance, and Repair Occupations), and 51 (Production Occupations). Sales, Personal care and Food Services include SOC codes 35 (Food Preparation and Serving Related Occupations), 39 (Personal Care and Service Occupations), and 41 (Sales and Related Occupations). Others include SOC codes 45 (Farming, Fishing, and Forestry Occupations), 53 (Transportation and Material Moving Occupations), and 55 (Military Specific Occupations).
Source: Data from all job ads posted on the portal during January 2014-June 2019.

Table B.3: Effect of Visa Regime on US-based Postings

	(1)	(2)	(3)	(4)
	Firm Panel		SOC Panel	
	Postings	Vacancies	Postings	Vacancies
Primary	-0.1768***	-0.1878***	-0.1652***	-0.1857***
	(0.0151)	(0.0171)	(0.0425)	(0.0471)
RFE	-0.2342***	-0.2534***	-0.2676***	-0.3011***
	(0.0118)	(0.0134)	(0.0444)	(0.0480)
Observations	57486	57486	13068	13068
R-Squared	0.277	0.273	0.524	0.512
Mean	0.0927	0.2883	1.3317	1.3317
Firm-Month FE	Yes	Yes		
SOC-Month FE			Yes	Yes

Notes: The table shows the change in US based vacancies and job postings advertized in India after Trump wins the Primary election. The dependent variable is log of vacancies and postings based in the US in a given firm-month-year in columns (1)-(2). The dependent variable is log of vacancies and postings based in the US in a given occupation-month-year (SOC-6 digit) in columns (3)-(4). To deal with zero values of the postings and vacancies we add a small value of 0.01 before taking the log transformation. *Primary* is an indicator variable equal to 1 for the period July 2016-March 2017 and 0 otherwise. *RFE* is an indicator variable equal to 1 for the period April 2017-June 2019 and zero otherwise. We keep firms and occupations that had at least one U.S. posting during this period in columns (1)-(2) and (3)-(4), respectively. Mean refers to the mean of the dependent variable without log transformation. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in parentheses are clustered at firm level in columns (1)-(2) and occupation level in columns (3)-(4). ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Data from all job ads posted on the portal during January 2014-June 2019.

Table B.4: Effect of Visa Regime on US-based Postings: Robustness (IHS)

	(1)	(2)	(3)	(4)
	Firm Panel		SOC Panel	
	Postings	Vacancies	Postings	Vacancies
Primary	-0.1183***	-0.1295***	-0.1177***	-0.1375***
	(0.0106)	(0.0127)	(0.0290)	(0.0342)
RFE	-0.1570***	-0.1764***	-0.1894***	-0.2230***
	(0.0084)	(0.0102)	(0.0313)	(0.0351)
Observations	57486	57486	13068	13068
R-Squared	0.283	0.275	0.553	0.535
Mean	0.0927	0.2883	1.3317	1.3317
Firm-Month FE	Yes	Yes		
SOC-Month FE			Yes	Yes

Notes: The table shows the change in US based vacancies and job postings advertized in India after Trump wins the Primary election. The dependent variable is the Inverse Hyperbolic Sine of vacancies and postings based in the US in a given firm-month-year in columns (1)-(2). The dependent variable is Inverse Hyperbolic Sine of vacancies and postings based in the US in a given occupation-month-year (SOC 2018-6 digit) in columns (3)-(4). To deal with zero values of the postings and vacancies we add a small value of 0.01 to postings and vacancies before taking the log transformation. *Primary* is an indicator variable equal to 1 for the period July 2016-March 2017 and 0 otherwise. *RFE* is an indicator variable equal to 1 for the period April 2017-June 2019 and zero otherwise. We keep firms and occupations that had at least one U.S. posting during this period in columns (1)-(2) and (3)-(4), respectively. Mean refers to the mean of the dependent variable without log transformation. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in parentheses are clustered at firm level in columns (1)-(2) and occupation level in columns (3)-(4). ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Data from all job ads posted on the portal during January 2014-June 2019.

Table B.5: Effect of Visa Regime on India-based Postings: Robustness

	(1)	(2)	(3)	(4)
	IHS		Log	
Panel A: Postings				
Primary × $Share_f$	0.0076***	0.0063***		
	(0.0016)	(0.0017)		
RFE × $Share_f$	0.0133***	0.0108***		
	(0.0017)	(0.0023)		
Primary × $Share_f \geq \mathbb{1}$[Median]			0.5048***	0.2884**
			(0.1382)	(0.1445)
RFE × $Share_f \geq \mathbb{1}$[Median]			0.8722***	0.4648**
			(0.1481)	(0.1923)
Observations	49764	49764	49764	49764
R-Squared	0.672	0.758	0.641	0.729
Mean	8.3237	8.3237	8.3237	8.3237
Panel B: Vacancies				
Primary × $Share_f$	0.0081***	0.0075***		
	(0.0017)	(0.0019)		
RFE × $Share_f$	0.0135***	0.0124***		
	(0.0019)	(0.0025)		
Primary × $Share_f \geq \mathbb{1}$[Median]			0.5526***	0.3384**
			(0.1488)	(0.1567)
RFE × $Share_f \geq \mathbb{1}$[Median]			0.9363***	0.5331***
			(0.1592)	(0.2059)
Observations	49764	49764	49764	49764
R-Squared	0.663	0.749	0.634	0.722
Mean	15.8539	15.8539	15.8539	15.8539
Firm-Month FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Firm-Month-Year Trends	No	Yes	No	Yes

Notes: The dependent variable is IHS transformation of India based postings (panel A) and vacancies (panel B) in a given firm in columns (1)-(2). The dependent variable is log of India based postings (panel A) and Vacancies (panel B) in a given firm in columns (3)-(4). In columns (3)-(4) we add a small value of 0.01 before taking the log transformation to deal with zero values of the postings. *Primary* is an indicator variable equal to 1 for the period July 2016-March 2017 and 0 otherwise. *RFE* is an indicator variable equal to 1 for the period April 2017-June 2019 and zero otherwise. *Share* captures the share of US postings among all postings by a firm in the period before the policy. $\mathbb{1}$[Median] is an indicator variable that takes a value of one for firms which have a higher than median *Share* and zero otherwise. We keep firms that had at least one US based posting during the pre-shock period. Mean refers to the mean of the dependent variable without log transformation. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in parentheses are clustered at firm level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Data from all job ads posted on the portal during January 2014-June 2019.

Table B.6: Effect of Visa Regime on India-based Postings: Alternative Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
	Postings (Levels)		Vacancies (Levels)		Extensive Margin	
Primary × $Share_f$	0.0212***	0.0286***	0.0341***	0.0640***	0.0016***	0.0009**
	(0.0061)	(0.0067)	(0.0125)	(0.0141)	(0.0003)	(0.0004)
RFE × $Share_f$	0.0439***	0.0579***	0.0690***	0.1252***	0.0024***	0.0012**
	(0.0073)	(0.0100)	(0.0142)	(0.0200)	(0.0003)	(0.0005)
Observations	49764	49764	49764	49764	49764	49764
R-Squared	0.723	0.791	0.680	0.748	0.558	0.648
Mean	8.3237	8.3237	15.8539	15.8539	0.5522	0.5522
Firm-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Month-Year Trends	No	Yes	No	Yes	No	Yes

Notes: The dependent variable is India based postings and vacancies in a given firm in columns (1)-(2) and (3)-(4), respectively. The dependent variable for column (5)-(6) is the extensive margin, a binary equal to 1 if a firm posted during a given month and 0 otherwise. *Primary* is an indicator variable equal to 1 for the period July 2016-March 2017 and 0 otherwise. *RFE* is an indicator variable equal to 1 for the period April 2017-June 2019 and zero otherwise. *Share* captures the share of US postings among all postings by a firm in the period before the policy. We keep firms that had at least one US based posting during the pre-shock period. Mean refers to the mean of the dependent variable. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in parentheses are clustered at firm level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Data from all job ads posted on the portal during January 2014-June 2019.

Table B.7: Effect of Visa Regime on India-based Postings: By Offshorability Potential

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Postings										
	Computer Related	Managers	Engineers	Finance & Business	Animation & Design	Legal	Other STEM	Healthcare	University	Community Work
Post × Share_f	0.0128***	0.0134***	0.0181***	0.0094***	0.0050**	0.0033	0.0114***	0.0058	0.0043*	0.0007
	(0.0025)	(0.0019)	(0.0052)	(0.0017)	(0.0025)	(0.0037)	(0.0036)	(0.0039)	(0.0025)	(0.0027)
Observations	40740	40200	25020	40860	28860	13500	24480	13380	18000	12000
R-Squared	0.591	0.593	0.519	0.550	0.401	0.411	0.460	0.431	0.364	0.309
Mean	2.3554	1.5472	0.6976	1.0880	0.3246	0.2129	0.4708	0.3358	0.1797	0.0986
Panel B: Vacancies										
	Computer Related	Managers	Engineers	Finance & Business	Animation & Design	Legal	Other STEM	Healthcare	University	Community Work
Post × Share_f	0.0132***	0.0140***	0.0193***	0.0098***	0.0048*	0.0032	0.0117***	0.0058	0.0040	0.0011
	(0.0027)	(0.0020)	(0.0056)	(0.0018)	(0.0026)	(0.0037)	(0.0037)	(0.0043)	(0.0026)	(0.0028)
Observations	40740	40200	25020	40860	28860	13500	24480	13380	18000	12000
R-Squared	0.591	0.596	0.518	0.551	0.402	0.411	0.460	0.440	0.365	0.309
Mean	4.2713	2.5241	1.2025	1.8876	0.5110	0.2700	0.7586	0.6647	0.3416	0.1715
Firm-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows the impact on India based postings of a firm by the pre-shock exposure of the firm to US based postings across different high skill occupations which combined account for almost 90% of the H1-B visas. The dependent variable is log of India based postings in a given firm (Panel A) and log of India based vacancies in a given firm-month-year (Panel B) for the occupation mentioned in the relevant column. To deal with zero values of the postings and vacancies we add a small value of 0.01 before taking the log transformation. *Post* is an indicator variable equal to 1 for the period July 2016-June 2019 and 0 otherwise. *Share* captures the share of US postings among all postings by a firm in the period before the policy change. Each column reports the results for a given occupation category. We keep firms that had at least one US based posting during the pre-shock period. Mean refers to the mean of the dependent variable without log transformation. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in parentheses are clustered at firm level. ***, **, * show significance at 1%, 5% and 10%, respectively.

Source: Data from all job ads posted on the portal during January 2014-June 2019.

Table B.8: Effect on India Postings: Robustness (Alternate Measures for Occupation Offshorability)

	(1)	(2)	(3)	(4)
	High WFH		Low Physical Proximity	
Panel A: Postings				
Post × Share$_f$ × High WFH	0.0046***	0.0042***		
	(0.0014)	(0.0014)		
Post × High WFH	-0.0519***	-0.0499***		
	(0.0187)	(0.0188)		
Post × Share$_f$ × Low Physical Proximity			0.0038***	0.0039***
			(0.0008)	(0.0008)
Post × Low Physical Proximity			-0.0578***	-0.0560***
			(0.0124)	(0.0122)
Observations	1171943	1165391	1171943	1165391
R-Squared	0.440	0.569	0.440	0.569
Mean	0.3016	0.3016	0.3016	0.3016
Panel B: Vacancies				
Post × Share$_f$ × High WFH	0.0047***	0.0042***		
	(0.0015)	(0.0015)		
Post × High WFH	-0.0512***	-0.0490**		
	(0.0197)	(0.0199)		
Post × Share$_f$ × Low Physical Proximity			0.0039***	0.0039***
			(0.0009)	(0.0009)
Post × Low Physical Proximity			-0.0582***	-0.0562***
			(0.0129)	(0.0128)
Observations	1171943	1165391	1171943	1165391
R-Squared	0.440	0.569	0.440	0.569
Mean	0.5055	0.5054	0.5055	0.5054
Firm-SOC FE	Yes	No	Yes	No
Firm-Month FE	Yes	No	Yes	No
Firm-SOC-Month FE	No	Yes	No	Yes
Firm-Year-Month FE	Yes	Yes	Yes	Yes

Notes: The table shows the impact on India based postings of a firm by the pre-shock exposure of the firm to US based postings and the degree to which Work from Home (columns 1-2) and low physical proximity (columns 3-4) is possible in a given occupation. The dependent variable is log of India based postings (Panel A) and vacancies (Panel B) in a given firm-occupation-month-year. The occupation is defined at SOC 2018-6 digit level. To deal with zero values of the postings we add a small value of 0.01 before taking the log transformation. Post is an indicator variable equal to 1 for the period July 2016-June 2019 and 0 otherwise. *Share* captures the share of US postings among all postings by a firm in the period before the policy change. *WFH* is the standardized measure for Work-From-Home index of occupation at SOC-6 digit level (Mongey *et al.*, 2021). *Low Physical Proximity* is the standardized measure for physical proximity*(-1) of an occupation at SOC-6 digit level (Mongey *et al.*, 2021). We keep firms that had at least one US based posting during the pre-shock period. Mean refers to the mean of the dependent variable without log transformation. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in parentheses are clustered at firm level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Data from all job ads posted on the portal during January 2014-June 2019.

Table B.9: Effect of Visa Regime on Additional Firm Outcomes in India

	(1) Exports	(2) Domestic Sales	(3) Profits
Post × $Share_f$	0.0056***	-0.0069	0.0049
	(0.0020)	(0.0072)	(0.0136)
Observations	219	205	219
R-Squared	0.950	0.933	0.893
Mean (in Thousands)	18.0476	11.5733	5.2472
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: The dependent variable is log of exports, log of domestic sales, and inverse hyperbolic sine transformation of profits for India-based firms in a given financial year. *Post* is an indicator variable equal to 1 for the 2016-2019 and 0 otherwise. *Share* captures the share of US postings among all postings by a firm in the period before the policy change (using the data from the job portal). We keep firms in Prowess which we could match by name with the job postings data and within them keep firms that had at least one US based posting during the pre-shock period. Mean refers to the mean of the dependent variable (in thousands) without log transformation. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in parentheses are clustered at firm level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: CMIE PROWESS Data from 2014 to 2019.

Table B.10: Spillover: Effect of Visa Regime on Postings in Europe and India

	(1)	(2)	(3)	(4)
	Europe: Exposed Firms		India: Non-Exposed Firms	
Panel A: Postings				
Post × USA Share$_f$	-0.0021	0.0016		
	(0.0033)	(0.0051)		
Post × Visa Share			0.0026***	0.0025***
			(0.0002)	(0.0002)
Observations	9504	9504	3002802	3002802
R-Squared	0.305	0.361	0.527	0.603
Mean	0.1326	0.1326	0.9910	0.9910
Panel B: Vacancies				
Post × USA Share$_f$	-0.0024	0.0013		
	(0.0037)	(0.0054)		
Post × Visa Share			0.0030***	0.0029***
			(0.0002)	(0.0002)
Observations	9504	9504	3002802	3002802
R-Squared	0.294	0.349	0.523	0.600
Mean	0.3798	0.3798	2.0734	2.0734
Firm-Month FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Firm-Month-Year Trends	No	Yes	No	Yes

Notes: The dependent variable is log of vacancies and postings in a given firm-month-year, in India and Europe respectively. To deal with zero values of the postings and vacancies we add a small value of 0.01 before taking the log transformation. Columns (1) and (2) include firms that post any vacancy in the US, and columns (3)-(4) include firms from India which do not have any postings in the US. *Post* is an indicator variable equal to 1 for the period July 2016-June 2019 and 0 otherwise. *Visa Share* captures the share of postings by a firm in occupations that are granted visa under the H-1B policy among all postings by a firm in the period before the policy change. *USA Share* captures the share of US postings among all postings by a firm in the period before the policy change. Mean refers to the mean of the dependent variable without log transformation. Each column reports the effective number of observations after incorporating the included fixed effects. Standard errors in parentheses are clustered at firm level. ***, **, * show significance at 1%, 5% and 10%, respectively.

Source: Data from all job ads posted on the portal during January 2014-June 2019.