Loss of Peers and Individual Worker Performance: Evidence From H-1B Visa Denials

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Abstract

We study how restrictive immigration policies and the unexpected loss of peers affect the performance of skilled migrants, exploiting the unexpected increased denials of H-1B visa extensions in the United States beginning in 2017. We find that employees who lost peers of the same ethnic background experience a substantial decrease in individual performance. To resolve the endogeneity surrounding visa denial decisions, we build an instrumental variable that exploits the fixed duration of the visas. Our mechanism tests suggest that ethnic ties boost individual performance through preferential channels of knowledge and information spillovers.

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1 Introduction

Immigration flows are increasing around the world, and the importance of immigrants as entrepreneurs and skilled employees in developed countries has been widely recognized by scholars (e.g., Kerr et al., 2017; Azoulay et al., 2022). In particular, companies are heavily reliant on skilled foreign talent: in the United States alone, foreign workers constituted more than half of the net increase in the labor force in science and engineering from 1995 to 2010 (Kerr & Lincoln, 2010). Immigrants account for a disproportionate share of the highly skilled U.S. workforce: almost 38% of workers holding a doctorate degree in science or engineering are foreign, despite foreign workers representing only 17% of the population.[1] Prior literature has also documented how skilled immigrants create value for organizations through the mechanisms of knowledge transfer (Wang, 2015), through knowledge recombination (Choudhury & Kim, 2019), and by organizations leveraging the networks of immigrants (Hernandez & Kulchina, 2020).

Nonetheless, immigrant workers are subject to a considerably higher probability of mutually involuntary separation from their firms, locations, and sectors than are other workers, on both the supply (employee) side and demand (employer) side. Several developed countries have in recent years embraced more restrictive immigration regulations, making it harder for skilled migrants to work in host countries (Rissing & Castilla, 2014; Choudhury, 2021). One of the most prominent examples of this is the Trump administration's adoption of the "Buy American, Hire American Act" in 2017, which substantially curbed the flow of high-skilled immigrants, including foreign-born academics to the United States, (Chinchilla-Rodrıguez et al., 2018). These changes were met with concern by many U.S. technology company CEOs, who were worried both about the negative consequences of losing foreign workers already employed at their companies and about their firms' inability to attract new high-skilled workers.[2]

[1] Figures refer to 2018. Sources: American Community Survey, 2018 Table B06009, and National Center for Science and Engineering Statistics, Table 7-2, available at https://ncses.nsf.gov/pubs/nsf21321/data-tables.

[2] "Trump's new travel ban raises the same Silicon Valley objections," *The Washington Post,* March 6, 2017 (available at: https://wapo.st/3ASViv7).

Thus, what happens when a worker is removed from a team, a firm, a location, or a sector without either side of the market (employee or employer) choosing this outcome is interesting in itself, in what it tells us about peer effects, substitutability, and production functions. And it is interesting in particular in the context of immigrant workers, who are especially subject to such separations. While prior literature has found evidence of a negative connection between more restrictive immigration policies and several economic outcomes at the regional level (e.g., Kerr & Lincoln, 2010; Clemens, 2011) and at the firm level (e.g., Bahar et al., 2020), it is unclear how stricter immigration policies influence individual worker performance within firms. On the one hand, given the well-established tendencies of diminishing marginal product (Clark, 1888; Clark, 1889) and hiring on the margin (Brooks Jr, 1974), the effect of losing a peer on the individual performance or output of workers who remain at the firm could be very small, or even positive. On the other hand, given the potential for knowledge spillovers in highly skilled workplaces, the effect of losing a peer on other workers could be large and negative. Understanding these effects within firms will be important for managers who need to adjust workplace composition and policies on the fly in the midst of ever-increasing immigration restrictions.

Given this gap in the literature, we ask how the unexpected loss of peers due to restrictive immigration policies affects the performance of individual workers remaining within firms. As ethnic ties have been shown to play an important role in moderating intrafirm dynamics and shaping performance (e.g., Hernandez, 2014; Kulchina & Hernandez, 2016), we also ask whether there are any differential effects on worker performance in losing a co-ethnic versus a non-co-ethnic peer. Beyond the skilled migration literature, our research questions are pertinent to the broader literature on organizations and economics that explores how peers shape worker performance (Mas & Moretti, 2009; Oettl, 2012).

In general, answering this question is challenging because of the inherent endogeneity of peer departure and the scarcity of detailed individual-level data within firms. In this paper, we overcome these obstacles by combining individual-level microdata and an unexpected change in immigration policies to show how exogenous changes in worker composition affect individual workers' performance within teams. We use data from a large Indian technology firm that employs around 150,000 workers globally, serving clients in multiple countries. We focus on Indian workers located in the United States, and we exploit different subethnicities within India to shed light on the role of ethnicity on peer performance. In 2017 and 2018, as a consequence of the "Buy American, Hire American Act," the United States unexpectedly began denying requests to extend temporary work visas (H-1B visas) at an unprecedented level.[3] Teams composed of H-1B visa workers began suddenly losing members.[4] By leveraging our detailed data at the individual and team levels combined with an objective measure of performance, we shed light on the consequences of the loss of a peer on individual performance within teams. Most important, by comparing individuals who lost peers of similar ethnicity to those who lost ethnically dissimilar peers, we investigate how ethnic ties moderate the relationship between stricter immigration policies and individual performance.

A key empirical challenge to causal identification is that visa denials might be correlated with some unobservable individual or team characteristics that might lead to potential biases in the estimation. For instance, it might be that less-educated and low-skilled employees have lower probabilities of getting their visas extended than more-educated and high-skilled workers. To address this issue, besides including individual fixed effects in all specifications, we exploit the bureaucratically fixed nature of the duration of an H-1B visa and the fact that some individuals were forced to go through the renewal process when denials were more likely to occur. Because extension timing is dependent solely on the H-1B visa's date of issuance, which is arguably exogenous, we use the ratio of the number of employees who had to file extensions to the total number of team members to create an instrument for the share of workers who experience visa extension denials. Estimates leveraging this instrument show that our results are robust.

Our results highlight how, on average, stricter immigration policies resulting in the loss of a peer tend to increase the individual performance of those left behind (Brooks Jr, 1974), despite the magnitude of these results being economically insignificant. However, this effect is reversed when losing a team member of the same ethnicity. In other words, same-ethnicity

[3] "Trump signs order that could lead to curbs on foreign workers," *The New York Times,* April 18, 2017 (available at: https://nyti.ms/34wThbE).

[4] Panel B of Figure A.1 in the Appendix shows the denial rate of H-1B extensions over time.

peers tend to increase each other's performance. Specifically, a 1% loss of same-ethnicity team members decreased an individual's performance rating[5] by about 2% compared to their performance prior to losing a team member. These results are robust to several checks that include the use of an alternate classification of ethnicity based on language, several pre-trend tests, placebo tests using other-ethnicity peers, and falsification tests in which the treatment groups and treatment periods are randomly selected. We also propose and rule out alternative theories that might explain our results. Overall, our main finding is robust, and we find no evidence of any spurious correlations that might bias our estimates.

We also explore which underlying mechanisms can explain our results. On the one hand, it might be that losing a co-ethnic peer hampers the flow of knowledge and information to other co-ethnic peers and more generally within the team. The superior flow of information and knowledge transfer among co-ethnic individuals is a well-established result in the literature—it has been found to have a profound impact on performance in a variety of settings (e.g., Kalnins & Chung, 2006; Kerr, 2008; Foley & Kerr, 2013; Hernandez, 2014). On the other hand, our results can be explained also by the mechanism related to social incentives and peer pressure in the workplace (e.g., Bandiera et al., 2009; Mas & Moretti, 2009). As co-ethnic individuals are more likely to form social ties (McPherson et al., 2001), their performance might particularly suffer from the depletion of "contagious enthusiasm" from the loss of a co-ethnic friend (Bandiera et al., 2010).

Heterogeneity analyses exploiting detailed team and worker characteristics suggest that our results can be explained by the reduction in knowledge transfer and learning occurring among co-ethnic peers rather than by social incentives. In particular, we can unequivocally shed light on this through two aspects: loss of peers by tasks and loss of peers by position. We find that: (i) only individuals assigned to atypical tasks experience decreases in their performance in response to the loss of co-ethnic peers; and (ii) the loss of co-ethnic peers substantially decreases the performance of junior workers, especially when a lost colleague was a co-ethnic supervisor. These two results highlight how co-ethnic individuals relying on irreplaceable knowledge and co-ethnic individuals dependent heavily on knowledge transfer processes are

[5] We define *performance rating* in Section 4, paragraph 2.

more exposed to the detrimental effects of peer loss. In addition, we find that individuals belonging to small teams or ethnically homogeneous teams are particularly affected by the loss of co-ethnic peers. Turning our attention to workers' individual characteristics, we find that the performance of male workers with relatively low salaries and low hierarchical positions within the firm declines the most after the loss of peers of the same ethnic background. Consistent with past literature (e.g., Azoulay et al., 2010), we also find that losing a high-performing co-ethnic peer is substantially more detrimental than losing a low-performing one.

This paper contributes to several strands of literature. First, it is connected to several studies examining the effects of tighter immigration policies and visa regulations on a variety of economic outcomes at different levels, especially those exploiting changes in the H-1B visa program. For instance, Doran et al. (2022) use lotteries and other identification strategies to find that hiring an H-1B visa worker causes firms to hire 1.5 fewer other workers, without affecting firm innovation. Kerr and Lincoln (2010) find that a reduction in the number of H-1B admissions decreases both immigrant and native patenting activity, while Peri et al. (2015a, 2015b) observe a reduction of tech-related employment and total factor productivity as a result.

Other works find similar negative effects of reducing H-1B admissions when comparing employment, sales, and profits of firms using the H-1B program versus those who did not (Mayda et al., 2020). Kerr et al. (2015) find that the employment of skilled immigrants increases the overall employment of skilled workers in firms. More recently, Bahar et al. (2020) find that Trump's executive order banning new work visas decreased the market valuation of public companies by roughly $100 billion. Our contribution here diverges by focusing on the effects of stricter immigration policies on within-firm dynamics and worker performance, looking specifically at the impact of restrictive immigration policies on individual workers.

Second, this paper is related to an increasingly large stream of literature that investigates how co-ethnic ties across and within organizational boundaries influence performance. For instance, Hernandez (2014) finds that co-ethnic communities facilitate companies' expansion to foreign countries. In particular, foreign subsidiaries leveraging co-ethnic ties were able to gain preferential access to the knowledge of foreign local communities, which reflected positively on their performance. Kulchina and Hernandez (2016) show how foreign firms managed by conational CEOs were able to obtain superior profitability compared to firms with non-conational CEOs when embedded in communities with large shares of co-nationals.

When investigating the role of ethnic ties within organizations, the evidence is more mixed and multifaceted. Lang (1986), for instance, argues that co-ethnic ties within organizations might improve performance because communication is facilitated due to linguistic similarity. This result is confirmed by Borjas et al. (2018), who find that the inflow of Chinese graduate students increases the productivity of Chinese advisors. Other works draw similar conclusions (e.g., Rauch & Trindade, 2002; Kerr, 2008; Nanda & Khanna, 2010). However, Freeman and Huang (2014) find that ethnic homogeneity within teams negatively affects production outcomes when examining the publication patterns and outcomes of U.S.-based scientific authors. In a similar vein, Choudhury and Kim (2019) notice how knowledge recombination is less likely to be pursued by teams composed of co-ethnics. Other scholars find that co-ethnic ties within an organization might be problematic, as they spur the emergence of interethnic rivalry and taste-based discrimination among non-co-ethnic peers, negatively affecting the performance of workers (Hjort, 2014). Differently from these studies, we focus specifically on *knowledge workers*, who nowadays represent the largest share of the workforce in every developed country (Drucker, 1999). Our findings also contribute to this literature by highlighting how co-ethnic ties have heterogeneous effects when examining different characteristics of teams and tasks, in line with the work of Marx et al. (2021).

Third, this paper relates to a vast and mixed literature documenting the effects of the loss or influx of peers. For instance, Borjas and Doran (2012) find that the influx of Soviet mathematicians into the United States had a negative effect on the productivity of U.S. mathematicians working on the same topics. Similarly, Azoulay et al. (2019) document that the death of an eminent scientist results in decreased productivity among coauthors but increased performance among noncollaborators in the field. Waldinger (2012) finds no impact on peer performance when investigating the dismissal of high-quality scientists in Nazi

Germany. When looking at the loss of scientists who have a propensity to be helpful, Oettl (2012) finds a negative impact on the performance of peers; however, the loss of scientists who do not display prosocial behavior does not influence the output of their peers.

Most of the prior work in this literature has focused on the loss of high-performance "star" scientists and academics on the performance of their peers. We take the research in this area forward by focusing on the loss of peers within firms. Most important, we aim to understand how ethnicity moderates the relationship between the loss of a peer and the performance of the remaining individuals.

The paper is structured as follows: Section 2 describes our conceptual framework, while Section 3 discusses the H-1B visa program. Section 4 describes the data and discusses our empirical specifications. Section 5 shows our results. Section 6 concludes. The Appendix contains further results.

2 Conceptual Framework

The loss of a peer may have significant consequences on the performances of workers left behind. On the one hand, the loss of a coworker might have a negative impact on the productivity of the workers left behind, as they might experience the loss of a key collaborator. On the other hand, one might expect to observe an increase in the productivity of workers left behind, especially if they are forced to compensate for the loss of their peer. In general, the literature examining the loss and influx of peers in a variety of settings has found mixed results. For instance, the arrival of Soviet mathematicians in the United States after the collapse of the Soviet Union decreased the productivity of U.S. mathematicians working in the same fields (Borjas & Doran, 2012). When investigating the consequences of the death of prominent scientists on the performance of other researchers, Azoulay et al. (2019) find that collaborators experienced a decline in the number of publications and grants received. When looking at the performance of peers after the dismissal of high-quality scientists in Nazi Germany, Waldinger (2012) did not observe a decrease in peers' performance.

In this paper, we aim to shed light on a new aspect of the phenomenon of peer loss, which has largely been overlooked by past literature: the loss of *co-ethnic* peers within teams. When thinking about how co-ethnic ties might moderate the relationship between the loss of team members and the performance of the remaining peers, we argue that two main mechanisms could be at play: knowledge transfer and social incentives in the workplace.

In the case of knowledge transfer, peers who have to unexpectedly leave their teams might stop contributing both "know-what" and "know-how" knowledge to their peers. We argue that this effect might be especially relevant for co-ethnic peers, who might preferentially share information within their own ethnic networks because of common frames of language and culture (Casella & Rauch, 2002; Koka & Prescott, 2002; Borjas et al., 2018). The existence of preferential channels of communication and knowledge transmission among co-ethnics is an established result in the literature that has been found in a variety of contexts. For instance, Kerr (2008) examines scientists and finds that foreign researchers of the same ethnicity cite each other 30% to 50% more frequently than scientists of other ethnicities. Other studies look at the importance of knowledge flows among co-ethnics in the context of multinational firms (Foley & Kerr, 2013; Hernandez, 2014), highlighting the role played by those co-ethnic communities in foreign countries. Still other studies emphasize this phenomenon while investigating cross-national trade (Rauch & Trindade, 2002) and cross-country citation patterns following scientists' movements (Oettl & Agrawal, 2008). These studies predict that losing a co-ethnic peer is likely to result in a decline in individual performance due to the decline of knowledge flows within teams after the worker's departure.

The second mechanism relates to social incentives and peer pressure in workplace environments. The notion that social relationships and workers' co-location might influence firm performance is a long-standing topic in the organizational behavior literature; it began to take shape in the seminal work of Mayo (1933), among others. More recent works have stressed the importance of worker interaction dynamics within firms. This literature suggests that the presence of certain individuals might enhance the performance of their peers through peer pressure, social incentives, and norms. Some studies have found how the presence of other workers, especially high-performing ones, induces social pressure, "contagious enthusiasm," and the desire to avoid social disapproval, leading to an increase in peer performance (e.g., Fehr & Falk, 2002; Ichino & Falk, 2005; Fehr & Goette, 2007; Mas & Moretti, 2009). Other works have instead highlighted the role of social preferences and relationships among workers, such as friendship and other social ties. For instance, Bandiera et al. (2010) show that employees' behavior is affected by the presence of other workers they are socially tied to; once again, this effect is moderated by the other workers' performance so that an employee's performance is greater when she works with friends who are more able than her and significantly lower when she works with friends who are less able than her. Generally, this literature would predict that workers sharing social ties might be particularly responsive to these dynamics. Given that co-ethnic ties are likely to motivate social incentives and social pressure (Portes & Sensenbrenner, 1993), losing a co-ethnic peer could result in a decline in individual performance.

We try to investigate which mechanisms are at play in our setting by exploiting a tightening of immigration policies that resulted in an unexpected increase in H-1B visa extension denials. In particular, the enactment of the "Buy American, Hire American" Act in April 2017 changed the H-B1 extension requirements, among other provisions.

3 The H-1B Visa Program and the "Buy American, Hire American" Act

The H-1B visa program, launched in 1990, allows U.S. technology companies and American subsidiaries of multinational firms to hire foreign-born, high-skilled immigrant workers. A foreign-born worker whose H-1B visa petition is approved is allowed to work in the United States for three years and is eligible to apply for a three-year extension. Applicants are allowed to petition for an extension only during the six months leading up to the H-1B expiration date. Because the number of H-1B visas is subject to an annual quota, the U.S. government (through the United States Citizenship and Immigration Services, USCIS) conducts a "computer-generated random selection process," commonly referred to as the "H-1B lottery," when the number of applications exceeds the total number of available visas.[6]

[6]The lottery is not conducted for H-1B visa extensions.

While the cap was generally not binding before 2004, it became binding in the following years. Since 2004, the cap has generally been met every year, while the lottery system has been in use since 2013.

In general, the application process for a new H-1B visa is costly and demanding. The petitioning employer has to meet strict requirements[7] and has to prove that the employee is qualified for a specialty occupation.[8]

The enactment of Donald Trump's "Buy American, Hire American" Executive Order on April 18, 2017, changed some of the regulations concerning nonimmigrant visas and also strengthened H-1B visa extension requirements in the name of protecting domestic workers. In particular, before this executive order, employers seeking visa extensions for their workers were not required to refile an entire H-1B application. The extension decision was based mostly on the information contained in the initial petition, and the burden was on USCIS officers to show a reason to deny the extension request. After the executive order was signed, employers were required to file complete applications, including supporting documents and workers' qualifications, to get their workers' visas extended. USCIS officers were required to scrutinize applications for extensions just as they would for initial visa petitions, shifting the burden of proof from the USCIS to the petitioner.[9]

After April 2017 the number of H-1B visa extension denials unexpectedly surged. Panel B of Figure A.1 in the Appendix shows the denial rate of H-1B extensions over time. Rejections more than doubled in fiscal 2018 (October 2017 to September 2018). Firms that depended on H-1B workers faced sudden decreases in their labor forces. In general, the denial rates

[7] Employers need to meet specific wage- and position-related requirements: they need to prove to the Department of Labor that they will pay wages to the H-1B nonimmigrant workers that are at least equal to the actual wage paid by the employer to other workers with similar experience and qualifications and that the position they are seeking to fill entails theoretical and practical application of highly specialized knowledge. Source: U.S. Department of Labor and USCIS.

[8] H-1B visa applicants need to prove they have a degree equivalent to a U.S. bachelor's or higher in the specialty occupation and have recognition of expertise through positions directly related to the specialty. Source: USCIS.

[9] The most common reasons for extension denials are linked to the failure to prove that the job falls under a specialty occupation, insufficient academic qualification, failure to fulfill the prevailing wage requirement in the occupation, and failure to provide third-party worksite evidence or to establish an employer-employee relationship.

experienced by the firm we study is highly correlated to the denial rates of other Indian firms (Panel C of Figure A.1).

Besides the increase in extension denials caused by increased scrutiny of work visa extensions, the act also caused increased denials of initial work visa applications and increased requests for evidence. The standards for petitions for H-1B employees who are supposed to work at third-party sites were strengthened. The act also modified some of the eligibility requirements for selected types of visas (L-1). Finally, it simplified the reporting of work visa fraud, expanded the collaboration between USCIS and the Department of Justice, and offered new tools providing information and statistics on employment-based immigration programs.[10]

In general, the H-1B visa program provides an ideal context to study our research question, given that it fulfills two conditions: (i) we can exploit the unexpected loss of peers using unexpected denials of H-1B extensions; and (ii) we can leverage variation in the ethnicity of workers leaving, given the heterogeneity of subethnicities of foreign workers holding H-1B visas.

4 Data and Methods

4.1 Data

We study the effect of more-restrictive immigration policies on individual and team performance by analyzing a single firm, a multinational technology company that employs around 150,000 workers globally and is active in several countries, including the United States, where it established a subsidiary in Silicon Valley in the late 1980s. In general, the company provides clients with solutions aimed at digitizing and streamlining IT processes for their clients. It serves multiple private and public players around the world, including several Fortune 500 companies, active in disparate industries ranging from pharmaceuticals to aerospace. This organization is the focus of our analysis.

[10] https://www.uscis.gov/archive/uscis-commemorates-second-anniversary-of-buy-american-and-hire-american-executive-order.

The company's employees tend to be assigned relatively skilled tasks, with the majority of the workers employed in programming and coding tasks that are aimed at integrating the existing client IT infrastructure with the modern and cost-effective IT solutions offered by the firm. The most common job roles within the firm are programmers and engineers (e.g., programmer analyst, system architect, and system analyst), followed by project managers. These individuals carry out a comprehensive set of tasks, such as coding, architecture design for cloud-based/software development projects, consulting tasks related to Salesforce implementation projects, and stack development. Within the firm, we can also find lower task-supporting roles, such as user support specialists, technicians, and systems administrators. These workers are assigned low-end business process management tasks, including managing call and contact centers and hardware/network infrastructure installation.

In general, managers assign workers to teams. Employees are periodically asked to list their skills based on prior experience and certifications. The company has a dedicated team that is in charge of matching open positions within projects to employees, based on the required tasks and employees' skills.

We collected data on personnel records, which include gender, age, department, and position for all 6,913 employees—all Indian nationals working on H-1B visas—whose initial H-1B petitions were approved. Information about workers' visa status is also sourced from internal HR records. We then constructed panel data related to their performance ratings and to denials of the H-1B visa extensions at the employee-year level. In our sample, applications, approvals, and denials of the H-1B visa extensions started in 2014, then denials surged during the Trump administration. Figure 1 shows the trend in denials of the H-1B visa extensions in our sample.[11] The increasing patterns are consistent with ones found in Figure A.1, which considers denials across all U.S. firms using administrative data.

The dependent variable in our analysis is the performance rating (hereafter, "rating") per year per worker, in an ordered index ranging from 1 (Needs Improvement) to 5 (Distinguished). This outcome is built on an objective measurement based on criteria such as client

[11] Once an employee's visa is denied, the worker is usually reassigned to the subsidiary, which is closer to his home location, and he is no longer involved with his old team.

satisfaction, ability to meet deadlines, and number of tasks completed, rather than on subjective supervisor evaluations. Employee ratings play an important role in our company, and they determine salaries, promotions, and terminations. While the initial salary is determined by the experience that the employee has accumulated before joining the firm, his/her future performance ratings might increase or decrease the base salary by 7%. Consistently positive performance ratings over time determine promotion within the firm. Figure 2 plots histograms of the average ratings in our data at the individual level and at the team-project level, while Figure A.2 in the Appendix provides a breakdown of ratings by year.

Employee characteristics, such as gender, age, and the Indian state of birth, are included in our data. We supplement these data with salary information from Glassdoor by matching the exact position within the firm and location. Though employees' ethnicities are not specified, we exploit the state of birth of each employee as a proxy for their ethnicity, and we define co-ethnics as people who share the same subethnicity within India. For example, employees born in Uttar Pradesh and employees born in Rajasthan are classified as being in the same ethnic group because they were born in North India and are very likely to share similar cultures and languages. By employing this geographical-based classification to identify employees' ethnicities, we obtain five main possible ethnicities (i.e., North, South, West, East, and Northeast India). Our results are robust to the use of other measures, such as a language-based classification. Table A.1 shows some summary statistics related to ethnicities while outlining our main categories; Table A.2 provides a breakdown at the individual, team, and business unit levels.

The geographical extent and historical background of India are reassuring about the generalizability of our results to contexts considering more traditional and "broader" ethnicities. The historical fragmentation and recent unification of the country have created a plethora of subcultures with their own religions, languages, and customs, all of which persist today. In particular, before India achieved independence in 1947, it was composed of several provinces controlled by local kings. The country was highly fragmented and exhibited significant cultural differences, such as in language, religion, and customs. After the country gained its independence, most of the states were formed by aggregating provinces that exhibited similar cultures and languages (Menon, 1955). In general, this led to the rise of powerful regionalism trends and the presence of no predominant ethnic groups within India. Due to its relatively recent independence, and the wide cultural heterogeneity among states that persisted over time, we argue that Indian subethnicities are akin to standard ethnicities that are often considered in the immigration literature.

Table 1 reports basic descriptive statistics for our sample, which is composed of 6,913 individuals observed from 2014 to 2018. The average individual employee rating is 3.4 (minimum of 1, maximum of 5).[12] In general, ratings are normally distributed, with employees typically achieving ratings of 3. The individuals in our sample tend to be relatively young males, with a mean age of 40. This is generally in line with the gender and age composition of the current U.S. science and engineering workforce, which is mainly composed of relatively young male employees.[13]

In terms of visa denials, roughly 44% of employees needed visa extensions during the period we analyze;[14] of these, 14% were denied. In the panel data at the employee-year level, which we use in our analysis, employees experienced the loss of 0.62% of their peers per year on average.

Employees are subdivided into 841 teams encompassing 187 business units. On average, each team has eight members. Figure A.3 shows the distribution of team size at the team and individual levels. The majority of the 841 teams are small, with the median team comprising two members, and a large number of teams are included in the first bin (i.e., teams with fewer than seven members). Figure A.4 highlights that most employees belong to teams with fewer than 50 members. A substantial share of employees (1,239/6,913 = 18%) is assigned to teams that have fewer than seven members (i.e., included in the first bin in our histogram). The median value is 28 individuals.

[12] This average is based on the whole sample of employees for the period 2008-2018.

[13] Sources: National Science Foundation, Science and Engineering Indicators 2018 and ACS (American Community Survey) 2019 (STEM and STEM-Related Occupations by Sex and Median Earnings).

[14] It is worth noting that the company always files visa extension applications for its workers every time a renewal is due, except in cases in which the worker leaves the firm or the country or experiences a change in her immigration status (e.g., receives a green card).

In Table 2, we report peer loss by team. Results show that most teams (705/841 = 84%) do not lose any members. Among teams that lose at least one member, the majority (75/136 = 55%) tend to lose only one member. When looking at the same statistic at the individual level (Table 3), we notice how peer loss is quite frequent when considering this unit of analysis. In particular, 61% (= 3,986/6,490) of individuals experience the loss of at least one peer, with most individuals (1,283/3,986 = 32%) losing exactly one peer.

Table 4 shifts the focus to peer loss by ethnicity. Panel A shows that workers who have lost at least one team member were more likely to lose a co-ethnic member: almost 70% (2,783/3,986) of individuals who lost a peer lost a co-ethnic peer. Panel B shows a detailed breakdown by co-ethnicity of the number of peers lost. In general, it is harder to distinguish between co-ethnic and non-co-ethnic losses within teams, as these are heterogeneous in nature. However, is it striking that all teams that lose a member (136 of 841) experience the loss of a peer who is co-ethnic with another member of the team.

4.2 Empirical Strategy

Our empirical strategy exploits variation in the decisions on H-1B visa extensions. We start our analysis by employing a naive difference-in-differences specification, and we supplement these models with instrumented specifications that tackle endogeneity-related concerns revolving around the selection of visa extension denials. In particular, in Section 4.3, we leverage an instrument exploiting the fixed nature of the visa renewal process and the fact that some workers had to undergo renewals in periods when denial rates were higher.

We consider two facts: that the applications could be approved or denied and that H-1B visa denials had been rising sharply during the Trump administration. We examine a sample of employees whose extensions were approved (or not filed because they were not up for renewal) and compare the subset of these who had team members whose extensions were denied (i.e., team members who were up for extensions but did not get denied and team members not up for extension—loss of peers) with the subset of these who had no team members whose extensions were denied (no loss of peers). We measure the causal effect of the loss of team members on performance in a difference-in-differences framework. Specifically, we employ the following specification:

$$Y_{it} = \beta PeerLoss_{it} + \theta X_{it} + \gamma_i + \tau_t + \epsilon_{it}, \tag{1}$$

where Y_{it} is the rating of employee i in year t and $PeerLoss_{it}$ is the number of H-1B extension denials in employee i's team (or business unit) divided by the initial[15] number of employees on the team (or in the business unit) multiplied by 100.[16] This variable measures the loss of peers due to visa extension denials as a percentage. We include the quartic of the age of person i in year t, the individual fixed effect γ_i, and the year fixed effect τ_t. We report the results from this estimation in Table 5, columns 1 and 3.

Now, we consider the loss of same-ethnicity peers in the following estimation:

$$Y_{it} = \beta PeerLoss_{it} + \alpha \left(PeerLoss_{it} \times SameEthnicity_i\right) + \theta X_{it} + \gamma_i + \tau_t + \epsilon_{it}, \tag{2}$$

where $SameEthnicity_i$ is a dummy variable equal to one if the lost team member in time t was of the same ethnicity of worker i and equal to zero if the lost team member in time t was of a different ethnicity than worker i. The coefficient α thus examines the effect of the loss of same-ethnicity peers due to visa extension denials. We report the results from this estimation in Table 5, columns 2 and 4.

Furthermore, we complement our empirical analysis with a difference-in-differences specification relative to the base year in an event-study framework:

$$Y_{it} = \sum_t \beta_t (PeerLoss_i \times D_t) + \sum_t \alpha_t (PeerLoss_i \times SameEthnicity_i \times D_t) + \theta X_{it} + \gamma_i + \tau_t + \epsilon_{it}, \tag{3}$$

where D_t is an indicator variable corresponding to a particular year t. The variable of

[15]That is, the initial team size before the occurrence of any visa extension denial. This considers only workers on H-1B visas, which represent more than 92% of the employees in our firm.

[16]Number of employee visa denials in employee i's team in year t divided by the number of members in employee i's team $\times$ 100.

$PeerLoss_i$ uses the total number of team members whose visa extensions were denied.[17] The β_t coefficients thus measure the effect of the loss of peers due to the visa extension denials relative to a base year, and the α_t coefficients examine the relative effect of the loss of the same-ethnicity team members.

4.3 Validity of the Identification

We investigate the validity of the identification by regressing variables that should not be affected by the result in the visa extension denial. H-1B visa extensions, in our sample, began to be filed and approved in 2014. Thus, we examine pre-trends from 2008 to 2013. Table 6 shows that differences exist in their ratings by their status in column 4, but these differences are not significant, as shown in column 5 when we regress other independent variables, including individual controls such as gender and age. In Panel A, we assess balance in baseline characteristics by comparing employees who lost one or more team members due to the visa extension denials with other employees who did not lose any team members before the visa extension decision. In Panel B, we compare employees whose visa extensions were filed but denied with other employees whose visa extensions were filed and approved. We also find no significant differences after controlling for individual characteristics.

The key identifying assumption of our difference-in-differences strategy is that the outcome of employees who had team members whose visa extensions were denied and the outcome of other employees who lost no such team members does not vary in the absence of extension denials. Figure 3 shows pre-trends of ratings among employees by their statuses from 2008 to 2013. We can then compare the average ratings of employees who had one or more team members whose visa extensions were denied (loss of peers) with the outcome for other employees who did not lose any members. Panel A shows common pre-trends based on raw data. Panel B presents coefficient estimates based on Equation 3 relative to the base year (2013): overall, no coefficients are significant for the pre-period. These tests provide

[17] We also estimate alternative specifications using a time-varying variable, $PeerLoss_{it}$, in an event-study framework, but it does not allow us to test our identifying assumption of common pre-trends, because the visa extension denials occurred from 2016 to 2018 in our sample. $PeerLoss_{it}$ takes a value of zero before 2016.

evidence of the validity of our empirical strategy. We also find no difference in pre-trends by comparing employees whose visa extensions were denied with other employees whose visa extensions were approved in Panels C and D. Finally, Table A.3 in the Appendix shows how treated and control individuals do not exhibit large differences when considering other observable features, such as age, gender, position, team size, and ethnicity. Overall, these findings affirm the validity of our identification strategy.

One might argue that visa denials could be correlated with time-varying and time-unvarying unobservable worker characteristics. For instance, it might be that less-skilled or less-experienced workers experience higher visa extension denial rates. If this bias was at play in our context, this might result in an underestimation in the magnitude of the $PeerLoss$. This means that, if anything, our OLS coefficients would be providing conservative estimates of the effect of a loss of a member on team performance. While the individual fixed effects in our main specification should take care of any correlations between the characteristics of peers left behind and the fact that workers experience the loss of a peer, there might still be some biases deriving from unobservable characteristics of workers and visa denials.

To assess whether this is the case, we instrument our original treatment variable by exploiting the fixed nature of the timing of H-1B visa extensions. Because the timing of the extension is fixed, based on the filing year of their first H1-B visa, we can consider it exogenous and orthogonal to workers' characteristics. Depending on the need to file extensions for their visas, workers will be differently exposed to the increase in the probability of denials. For instance, a worker who had her visa renewed just before the start of the surge in denials will be less at risk than a worker who is due to renew her visa in the years where denials increased. Leveraging the fixed nature of visa denials, we build an instrument by considering the number of peers who filed an extension (in a given year) on team size. Formally, we estimate the following first-stage and instrumented equations:

$$
\begin{cases}
LossPeer_{it} = \beta FiledPeer_{it} + \theta X_{it} + \gamma_i + \tau_t + \epsilon_{it} \\
Y_{it} = \beta \widehat{LossPeer}_{it} + \alpha \left(\widehat{LossPeer}_{it} \times SameEthnicity_i \right) + \theta X_{it} + \gamma_i + \tau_t + \epsilon_{it},
\end{cases}
\tag{4}
$$

where $FiledPeer_{it}$ is our proposed instrument.

5 Results

5.1 Denials and Peer Performance

We examine how more-stringent immigration policies resulting in the loss of team members due to visa denials affect team members' performance. Table 5 reports the results of our difference-in-differences specification (Equation 1) using ordinary least squares (OLS). We report results using two types of samples: an unbalanced sample that considers the 2008–2018 period, for which some information is missing,[18] and a balanced sample that considers the 2014–2018 period. The models using the balanced sample are our preferred specifications. The coefficient ($PeerLoss$) in column 1 suggests that the visa denials of team members on the project team increased other team members' performance. This finding suggests that a 1% loss of peers due to visa denials at the project-team level increased ratings by 0.008. Specifically, for employees whose ratings were observed from 2014 to 2018 (in column 1), a 0.008 increase in rating was attributed to a 1% loss of peers due to visa denials. Given the average rating of 3.610 in our balanced sample, a 1% loss of peers increased individual performance by 0.2%. On the average project team with eight members, losing one peer (i.e., a 12.5% decrease in team members) leads to a 2.7% increase in performance of those left behind. Despite the coefficient being positive and statistically significant, the magnitude of the coefficient is small and economically insignificant.

When investigating the roles ethnic ties play in this framework, we find a striking reversal of

[18] Despite the data on ratings going back to 2008, we have data about visa extensions only from 2014 onward.

our initial result: the loss of co-ethnic peers due to H-1B visa denials substantially decreases the performance of other team members. Column 2 in Table 5 shows a negative and significant coefficient for the interaction term ($PeerLoss \times SameEthnic$). Our results suggest that a 1% loss of team members due to visa denials decreased ratings by 0.058 (1.6%) within teams.[19] On the average project team with eight members, losing a same-ethnicity peer decreased the individual performance of those left behind by 20%. When considering standard deviations, an increase in the loss of co-ethnic peers of one standard deviation would decrease performance ratings by 0.3%. The loss of roughly one-third of co-ethnic peers, which corresponds to going from the minimum to the maximum value of *PeerLoss*, decreases ratings by 53.3%. Figure 4 shows how the predicted rating of peers varies as the number of lost co-ethnic and non-co-ethnic peers increases. In general, the unbalanced panel shows consistent results: the coefficients in column 4 suggest that peers decreased their performance by 0.072 (2.1%) when losing a co-ethnic peer.

Consistent with the results shown in the previous tables, Panel A of Figure 5 shows the coefficients on the interaction term ($PeerLoss \times SameEthnic$) interacted for each year relative to the base year 2014 in Equation 3. This figure suggests that the negative effect on performance in our sample occurred in response to the loss of the same-ethnicity peers when the visa extension denials surged in 2017 and 2018. The results also provide evidence on the identifying assumption of parallel trends in performance of workers who lost peers and those who did not before visa denials surged in 2017. Panel B of Figure 5 shows the dynamic effects relative to a year before the loss of the same-ethnicity peers (where time 0 represents the year a co-worker's visa extension is denied). We find that the results are robust to this specification.

To make sure that visa denials are orthogonal to workers' and teams' time-varying characteristics, we instrument the ratio of visa denials with the instrumental variable described in Section 4.3—that is, the share of visa extensions on team size. In general, this instrument is highly correlated with our endogenous variable: the coefficient of the first stage is

[19] If we use the average of *PeerLoss* among teams that had any denials in the calculation of our magnitude, we find that a 1% loss of co-ethnic peers due to visa denials decreased ratings by 0.0533 (1.48%) within teams.

0.067 with a standard error of 0.011, which translates to a 1% significance level. Table 7 shows the results of the instrumented specification presented in Equation 4, where we instrument $PeerLoss$ and the interaction ($PeerLoss \times SameEthnic$) with the number of peers who needed to file visa extensions on team size (i.e., $FiledPeer$) and its interaction with $SameEthnic$ (i.e., $FiledPeer \times SameEthnic$). All specifications exhibit strong F-statistics, which are consistently higher than 10.

When looking at both balanced and unbalanced samples, our main OLS results are confirmed: the loss of co-ethnic members negatively impacts the performance of peers left behind. Columns 1 and 2 exhibit, in general, a slightly lower coefficient for $PeerLoss$, which results in the main effect no longer being significant in column 1, despite being very close to the 10% level of significance. This suggests that our estimates for the coefficient $PeerLoss$ were slightly underestimated. As hypothesized above, this bias may come about from less-skilled or less-experienced workers being more likely to have their visa extensions denied. However, the coefficient for the interaction ($PeerLoss \times SameEthnic$) in our preferred specification included in column 2 is *not* statistically different from the one found in our OLS specifications (column 2 of Table 5). The results in our unbalanced models seem to confirm our main results.

While in our main model we use a proportional treatment (the proportion of team members whose visa extensions have been denied on team size multiplied by 100), it might be helpful to show results leveraging a much simpler treatment using a dummy variable indicating whether a worker has experienced the loss of at least one peer. Table A.4 in the Appendix shows our main specification using a dummy capturing whether the individual has experienced the loss of at least one member as the treatment variable. We report standard errors clustered at the team and individual levels for completeness. Column 1 shows the effect of the loss of at least one member on peers' performance. Column 2 introduces the interaction (*PeerLoss* x *SameEthnic*). In general, results are robust, despite the borderline insignificance of the interaction term when clustering standard errors at the team level.

As a further robustness check, we run our main specification using a different aggregation level for our treatment variable—that is, we aggregate our treatment variable at the business unit level. Table A.5 shows how our results are consistent with this alternative treatment variable. Interestingly, the loss of an employee is no longer associated with an increase in performance. However, the loss of a co-ethnic team member still has significant and negative effects on peer performance, suggesting not only that the consequences of visa denials are experienced at the team level, but also that they can have a ripple effect throughout a firm's business units. This result also hints that even though some team members experience an increase of performance at the individual level after the loss of a peer, these gains are not enough to compensate for the drop in performance of the co-ethnic workers left behind. Figure A.5 in the Appendix shows the coefficient of the interaction ($PeerLoss \times SameEthnic$) over time relative to 2014 and 2013.

5.1.1 Additional Robustness Checks

Because our dependent variable is an ordered index of ratings, ranging from 1 (Needs Improvement) to 5 (Distinguished), we also employ an ordered logit model as an alternative specification. Table A.6 in the Appendix shows that the results are robust: same-ethnicity peers matter for employees' performance. Results from these specifications suggest that the odds of a higher rating versus a lower rating are 1.03 times greater for workers in a project team who lost some team members than for workers who did not lose any peers (column 2). However, the odds of a higher rating versus a lower rating are 0.86 times lower for workers who lost co-ethnic peers than for other workers.

As a further robustness check, we conduct a placebo test that addresses the possibility of a spurious correlation between the loss of same-ethnicity peers and the outcome variable. We exploit the fact that employees could lose peers with different ethnicities from theirs, and we use these non-co-ethnic peers in a placebo test to check the robustness of our main findings. If the effect of the loss of peers on performance is indeed driven by the loss of co-ethnic peers, we would expect no significant effects of losing peers from other ethnic groups. Columns 2 and 4 of Table A.7 in the Appendix show the insignificant coefficients on the interaction term ($PeerLoss \times OtherEthnic$) according to modified Equation 2. The loss of non-co-ethnic peers due to the visa denial is not sufficient to affect performance, suggesting that the loss of co-ethnic peers is key in decreasing team members' performance.

We also conduct a falsification test in which the treatment groups and treatment periods are randomly selected. In our sample, 283 employees who filed H-1B visa extensions were denied. We randomly choose 283 other employees as a placebo treatment group, without replacement, and construct a new right-hand side variable. We then reestimate the regression in Equation 3 and report the coefficient on ($PeerLoss \times SameEthnic$) of the placebo treatment variable. We repeat this test 10,000 times with random shuffles. Figure 6 shows the distribution of the coefficients resulting from every iteration. The solid line shows the actual causal effect using the true data. If we calculate a p-value using the proportion of the 10,000 iterations where we find coefficients smaller than the true estimate (located to the right of the solid line in the graph), we obtain a p-value of $< .001$. In general, both falsification tests alleviate concerns that our results are being driven by spurious correlations.

In order to verify the validity of our instrument, we conduct a third placebo test that checks whether the performance of workers who did not lose any team members is impacted by the filing of an extension by a member of the team. Table A.19 in the Appendix shows the results of this exercise while using our baseline sample (columns 1 and 3) and the sample of individuals who did not lose any peers (columns 2 and 4). As expected, the coefficients in columns 1 and 3 are significant, while the ones in columns 2 and 4 are not, thus reassuring us of the validity of the instrument and the exclusion restriction.

Finally, we check whether our results are particularly sensitive to the exclusion of one of a few states. Given that most of the employees in our sample come from Tamil Nadu and Uttar Pradesh, we run our baseline specification while excluding these groups. Table A.8 in the Appendix shows how our results are robust to the omission of these groups.

5.1.2 Alternative Explanations

Ethnicity classification. We might be worried that our measure of ethnicities based on the Indian state of birth does not accurately capture ethnicity, which usually encompasses several other components such as culture, language, and shared norms. In particular, it might be that, given India's high cultural fragmentation, the state of birth might capture ethnicity imprecisely. We thus build an alternative measure of ethnicity classifications using the language of employees' native states. Table A.1 shows that, in general, the geographical classification and the linguistic classification are somewhat correlated. When assessing our main results using this alternative classification, we find that the results are, in general, robust (Table A.9): employees' performance decreased when they faced the loss of co-ethnic peers who could speak their own language.

Other types of homophily. One might suspect that the ethnic ties we are capturing are confounded with other types of homophily, such as gender or age. Table A.10 shows our main specification, where we interact $PeerLoss$ with other homophily-related variables. In column 1, we report our baseline specification using ethnicity; in column 2, we assess whether losing a team member of the same gender has an effect on peers; in column 3, we take into account different age groups. Finally, in column 4, we include all the previous interactions. The insignificant estimates in Table A.10 suggest that the loss of same-gender peers or the loss of same-age group peers does not affect the performance of remaining team members.[20] Sharing the same ethnicity is what matters when it comes to peer performance.

Change in ethnicity composition as a response to visa denials. Differences in a team's ethnic diversity raise possible concerns. Specifically, it is possible that the firm responds to visa extension denials by varying, and most likely diminishing, the number of foreign workers employed at the firm, which would affect teams' ethnic diversity over time. Though individual fixed effects in our regression models mitigate concerns related to

[20]In general, 99 teams experienced the loss of a man, while 15 teams experienced the loss of a woman. And 103 teams experienced the loss of a peer of the same gender (i.e., at least one man or one woman on the team experienced the loss of a member of the same sex), while 72 experienced the loss of an opposite gender member (i.e., at least one man or one woman on the team experienced the loss of a member of the opposite sex).

particular individual characteristics (such as gender, age, and position), the change in ethnic diversity over time is not accounted for. Therefore, we run our main specification while including two additional time-varying measures that account for changes in ethnic diversity over time. We calculate the proportion of same-ethnicity peers over time, and we build an ethnolinguistic fractionalization (ELF) measure constructed as one minus the Herfindahl index of ethnic group shares.[21] Table A.11 shows that the results are robust to controlling for potential confounding effects of time-varying ethnic diversity.

Employee turnover. One might be worried that the decrease in performance that we observed could be caused by employee turnover. It could be that some employees decide to leave their firms once they lose peers. We thus assess whether the loss of team members is correlated with turnover in any way. Table A.12 shows no impact on turnover, meaning that the loss of peers, regardless of ethnicity, did not push other employees to leave the firm.

Motivational loss. It could be that some employees lose motivation after the departure of co-ethnic colleagues due to visa denials. As scholars have found uncertainty to have a decreasing effect on performance in a variety of settings (e.g., Bloom, 2014), some employees might decide to decrease their exerted effort as a response to a higher perceived risk of future visa denial. Though past research has found that nationality plays an important role in influencing visa approvals (Rissing & Castilla, 2016), this has not been found true for state of birth within countries. Since our sample is composed of all Indian nationals, we believe that this alternative explanation is unlikely to play a role in this setting, given that all employees have the same baseline probability of having their visas denied. If this motivation-related explanation was at play, we should observe a decrease in performance for both co-ethnic and non-co-ethnic colleagues.

One might also argue that motivational loss might occur among workers of the same subethnicities if some Indian states are disproportionally targeted by denials. If so, it might be that workers belonging to a given subethnicity might perceive to be more at risk than other employees. Table A.13 shows how denial rates are, in general, stable across subethnicities,

[21] Specifically, $ELF_j = 1 - \sum_{i=1}^{N} s_{ij}$, where s_{ij} is the share of group i in team j, the Herfindahl index of ethnic group shares.

highlighting how this phenomenon is not likely to be at play in our context.

To make sure motivational loss does not play any role in our setting, we rerun our baseline model while considering only workers who have just been approved or workers who do not need to extend their visas because of a change in their immigration status. Table A.14 reassures us that motivational loss is not driving our result.

Subethnicities and state characteristics. One might argue that the ethnicities we capture are simply picking up social and economic differences between regions that could be driving our result. To make sure this is not the case, we run our baseline model while including a set of controls at the birth state level, capturing a host of socioeconomic features such as population, GDP, employment rate, percentage of literate individuals, percentage of individuals with bachelor's degrees, percentage of individuals with technical degrees, percentage of Hindu individuals, and percentage of Muslim individuals. Table A.15 shows the results of our main specifications while including a set of state-level controls. It is reassuring that the signs and magnitudes of the coefficients in the balanced and unbalanced regressions are very similar and not statistically different from those found in our baseline regressions (Table 5). Overall, this reassures us that the co-ethnicity coefficient (*Same Ethnicity*) is not capturing some unobserved underlying characteristics at the birth state level. This also reassures us of the absence of selection into identification-related phenomenon (Miller et al., 2019) in our empirical framework, as it might be that ethnicities and more generally states of birth are correlated with some unobservable underlying characteristics (such as education) which, in turn, are correlated to whether workers will experience visa denials.

5.2 Interpreting the Findings

We try to shed light on which underlying mechanisms—knowledge flows versus social incentives—are driving our results. To do so, we examine how team- and individual-level characteristics affect the performance of workers in response to the loss of peers whose H-1B visa extensions were denied. We investigate this by using individual ratings aggregated at the team level while splitting employees into different subgroups based on team-level characteristics and individual-level characteristics. Among the several characteristics that we can leverage, two features appear to be particularly promising to clarify which mechanisms might be driving our results: team task type and hierarchical position of the departing and remaining peers.

First, we try to tease apart our two mechanisms by examining the type of tasks that have been assigned to each team. If knowledge transmission plays a role in determining the decline in peer performance, then teams that have been assigned tasks that require knowledge that is not easily replicable and cannot easily be replaced within the firm (i.e., knowledge that is most likely "tacit," Polanyi (1961)) should experience greater drops in performance than teams dealing with more trivial and routine tasks. But, if social incentives were to drive our results, we should not expect a difference in performance when considering these two groups of teams because social incentives should not be particularly influenced by the tasks performed by team members.

To classify tasks as either "typical" or "atypical," we leverage information about team names. We infer task uniqueness by assessing how similar team names are within the organization.[22] Specifically, we use Jaccard's similarity index on team name similarity, and we examine the effect of a loss of a co-ethnic peer separately for teams with low and high task uniqueness (using the median as the reference). The rationale of this measure relies on the fact that teams with relatively common names will most likely perform typical tasks—that is, routine tasks or tasks that require knowledge and skills that can be easily replaced within the company. For instance, there are roughly 90 teams in our sample that were dedicated to "infrastructure services delivery;" their names are all slight variations of "ISD US DEL" (e.g., "ISD US DEL NORAM1," "ISD US DEL NORAM2"). These teams performed similar tasks, which we classify as "typical" for the company. Other teams perform unique tasks, which we classify as "atypical." For instance, there is only one team in charge of communication with external customers. If this team were to lose a member, the organization might not readily replace her knowledge and skills. Table 8 shows that the negative effect of the loss of co-ethnic peers is only present if we consider teams with atypical tasks, suggesting it

[22] All the teams in our sample had dedicated technical tasks, and no teams were assigned administrative tasks or tasks that might be unique, because they were broadly shared within the organization.

is the loss of knowledge and skills, rather than social incentives, that drives the decline in performance of co-ethnic members.

Second, we investigate the loss of team members by position. The loss of team members holding different hierarchical positions within a team might affect the remaining members in various ways. For instance, if social incentives played a role, we would expect that employees in junior positions who lose junior peers might be more likely to suffer a drop in performance than employees in senior positions, given that social ties are more easily formed by workers with a similar level of seniority. Instead, if we found that junior employees are more affected by the loss of supervisors, then it would be plausible to hypothesize that a decline in performance might be caused by a drop in knowledge transmission, as junior employees may be particularly more reliant on their supervisors' knowledge and skill. We first categorize each employee as junior or senior based on position level.[23] Then we analyze the impact of a loss by classifying departing and remaining team members by position.

Table 9 presents the results from this analysis. Columns 1 and 2 show that the loss of co-ethnic peers substantially decreased the performance of junior workers, especially when the lost colleagues were co-ethnic supervisors. This is once again evidence that knowledge transfer and learning among team members seem to play much more prominent roles than social incentives in explaining our results. Despite the fact that co-ethnic junior employees might be more likely to form social ties with other junior colleagues, they seem to suffer the departure of co-ethnic supervisors more. Columns 3 and 4 show that senior employees are not significantly affected by the loss of other team members, regardless of ethnic similarity. This can be explained by the fact that supervisors already possess sufficient knowledge and skills and are not particularly affected by the loss of other knowledgeable supervisors or junior employees. Overall, our evidence points unequivocally at the fact that impaired and weakened knowledge flows, rather than social incentives, drive the decrease in performance of co-ethnic members.

[23] We define junior workers as entry-level employees and software engineers. We consider all other workers as senior employees, who occupy the following positions: team leaders, project managers, general managers, directors, associate vice presidents, vice presidents, and senior vice presidents.

It might be possible that the effect we find is related to a kinship-related dynamic for which supervisors decide to sponsor and champion junior peers of the same ethnicity. If this mechanism is at play, we should observe a drop in junior employees' performance independently of which tasks the team has been assigned. Table A.16 in the Appendix shows how only junior employees who lost their supervisors assigned to teams with atypical tasks experience a reduction in their performance.

Having clarified which mechanism is responsible for driving our results, we exploit the remaining individual- and team-level information at our disposal to show how the loss of peers can influence the performance of the remaining workers. The results from these analyses can be extremely valuable from managerial and policy points of view, as they highlight which teams and workers are more exposed to the loss of co-ethnic peers.

We start by examining two team-level features: team size and team diversity.

In general, there exists a sufficient variation in peer loss within small teams, with 31% of individuals in small teams losing at least one member and 19% of individuals in small teams losing at least one co-ethnic member (see Table A.17 in the Appendix). Table 10 shows that the negative effects of the loss of co-ethnic peers are generally driven by workers in small teams.[24] This is also confirmed by Figure A.6 in the Appendix, which shows the average marginal effect of loss of peers by team size and maximum team size. Only teams smaller than 15 workers experience performance decreases after the loss of co-ethnic peers.

Table A.18 in the Appendix shows the results from our usual baseline regression by team size using various thresholds, thus confirming that our main results are not affected by the definition of small teams. In Panel A, we show the effect of peer loss on small teams; Panel B shows the same estimates while considering large teams. In columns 1 to 6, we use different thresholds to define small and large teams (i.e., below and above the 25th, 30th, 40th, 60th, 70th, and 75th percentiles, respectively). Results appear to be robust.

[24] Note that team size is not particularly helpful in tearing apart the mechanisms—both of our proposed mechanisms suggest that workers in small teams may be more affected by the loss of their co-ethnic peers. On the one hand, members of a small team might be more socially tied to one another, which might increase the importance of social incentives in the workplace; on the other hand, the loss of knowledge and expertise of a member might more negatively affect a small team than a large team.

Columns 3 and 4 in Table A.4 show the usual specifications while considering a dummy variable treatment instead of the usual proportional treatment. These regressions confirm that our results are driven mostly by small teams.

Turning to team diversity, Table 11 shows that workers belonging to less ethnically diverse teams experienced stronger negative shocks than workers in more ethnically diverse teams. This might be supportive of our knowledge-related mechanisms, given that, after the loss of co-ethnic individuals, more members in homogeneous teams would suffer decreases in the levels and quality of information flows. As roles tend to be heterogeneous within teams and members need to communicate with one another to coordinate diverse tasks, we would expect more members to suffer once co-ethnic peer loss occurs, as multiple communication and knowledge channels get damaged.

Besides leveraging team features, we can also explore possible heterogeneous effects using individual characteristics. When considering age, Table 12 shows how young and old workers are similarly affected by the loss of same-ethnicity peers; however, we notice significant negative effects in particular for male workers (Table 13) and workers with low salaries (Table 14).

Turning our attention to worker quality, 59 of 430 teams experienced the loss of high-performance members. This number lowers to 53 when considering teams that experienced the loss of high-performance co-ethnic peers. Table 15 shows that the loss of high-quality co-ethnic peers (i.e., consistently high-performing team members) has a larger negative effect than the loss of low-quality team members.[25] This result is consistent with a large literature examining the effect of the loss of "star" members on teams (e.g., Azoulay et al., 2010) and with our knowledge-based mechanisms, given that high-performing individuals might possess superior knowledge on average.

[25] We define a high-performing worker as an employee whose average rating is higher than the rating assigned to her team before the period of our analysis (i.e., before 2014).

6 Conclusion

This paper studies how the unexpected loss of peers due to restrictive immigration policies affects the individual performance of skilled migrants. By leveraging unique microdata from a large firm that contains detailed information about workers' visa status and by exploiting the exogenous departure of team members due to work visa denials, our results show that individuals who lost peers of the same ethnicity experienced significant decreases in their performance. We shed light on the mechanisms underlying these results by exploiting a rich set of characteristics at the team and individual levels and by examining who suffers the most from the departure of co-ethnic team members.

We find that small teams, teams working on atypical tasks, and ethnically homogeneous teams are more sensitive to the loss of peers. When looking at individuals, we find that male workers with low salaries and low positions within their firms suffer the biggest performance drops when co-ethnic team members leave, especially if the leavers occupy relatively high positions within their teams. Our heterogeneity results suggest that the decline in performance we observe for co-ethnic workers can be explained by a deterioration of knowledge flows and information spillovers within teams, rather than by a decrease in social incentives.

Many papers in the literature on the effect of immigration restrictions on sectors, locations, and firms highlight how differences between immigrants and natives can bring about complementarities that cause immigration changes to have disproportionate effects on outcomes. Our study instead highlights a mechanism that has not yet been examined within firms: how co-ethnic similarity between immigrants and each other can create preferential knowledge channels that are sufficiently powerful that they also cause immigration changes to have disproportionate effects on outcomes.

Our study is not exempt from limitations. First, despite the richness of our data, we focus on workers within just one firm. Second, the generalizability of some of our results could be limited by the fact that our workers are foreign born. It is unclear whether the mechanisms at play in our context also apply broadly to native employees. Third, lack of data and the Covid pandemic prevent us from studying the long-term effects of peer loss. Finally, we capture ethnicities within a single country. Future research could go beyond these limitations by trying to replicate our results in other contexts and settings. For instance, it would be valuable to study native workers or examine employees with different backgrounds and education. Future research could also focus on other countries to shed light on the role of culture on within-firm dynamics and workers' performance. Further research could also be dedicated to examining what happens to the productivity of workers who are forced to leave their teams. This might improve our understanding of the consequences that tighter immigration policies have on subsidiaries of multinational firms.

One area where our results are relevant is informing challenges related to managing foreign talent in light of tighter immigration policies. Recently, companies that have been historically reliant on foreign workers, such as Infosys and Tata Consultancy Services (TCS), have been forced to increase their share of native workers to deal with increasingly unstable immigration scenarios.[26] Other companies are instead responding to these changes by reassigning foreign workers who can no longer remain in the United States to their foreign subsidiaries, so that they can reenter the States after a few years under a new nonimmigrant visa.[27]

By shedding light on which workers are most vulnerable to the loss of peers, our paper also offers important implications for managers who have to face the consequence of tighter immigration policies in their teams and departments. Our results highlight how workers within teams that rely on specialized knowledge, which cannot be easily replaced or replicated within the firm, are the ones that suffer the most from the departure of a co-ethnic member. Also, workers belonging to teams where employee learning is fundamental, and junior workers who are reliant on the knowledge of their surrounding teams, are particularly exposed to the effect of tighter visa regulations.

As more and more companies in the knowledge-based economy rely on foreign talent, a deeper understanding of how changes in immigration policies affect workers' performance

[26] See for instance Infosys' press release from September 1, 2020. Available at: https://infy.com/3ryO1O4.

[27] "Silicon Valley is making plans to move foreign-born workers to Canada," *TechCrunch,* January 31, 2017. Available at: https://tcrn.ch/3B5aTrA.

within firms is needed. Shedding light on this topic is particularly salient considering that knowledge-intensive companies are responsible for more than half of the GDP in all developed countries.[28] By studying the impact of stricter immigration policies on individuals working within heterogeneous teams and departments employing foreign workers, we have highlighted the important role that privileged knowledge channels among co-ethnics play within firms. These findings imply that tighter immigration policies can halt critical knowledge flows within organizations and inadvertently harm the performance of employees in specific teams and departments. In conclusion, our study provides an important, unexplored piece of evidence related to the debate on protecting or restricting the H-1B program.

[28]Source: OECD (2000g), Science, Technology and Industry Outlook, Paris.

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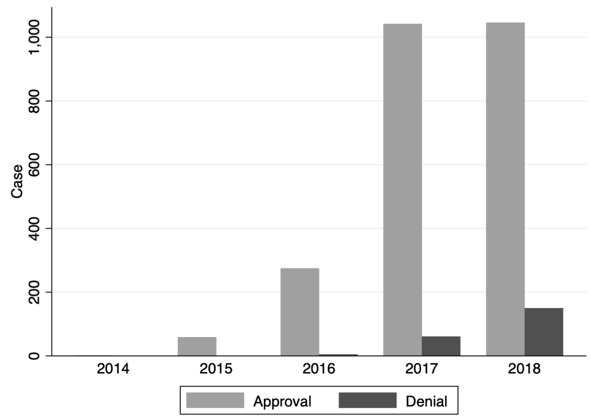
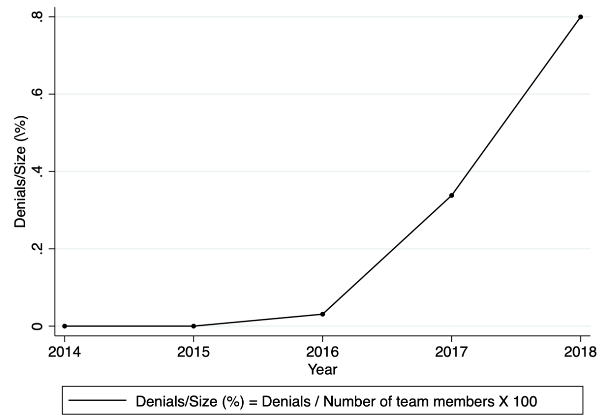
Figures and Tables

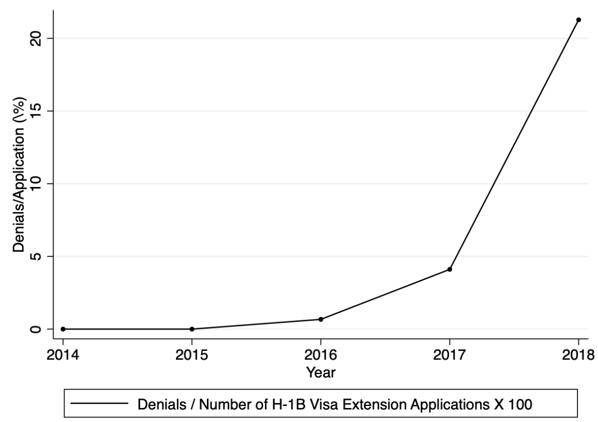
Figure 1: H-1B VISA EXTENSION DENIAL IN OUR SAMPLE



(a) Visa Approvals and Denials



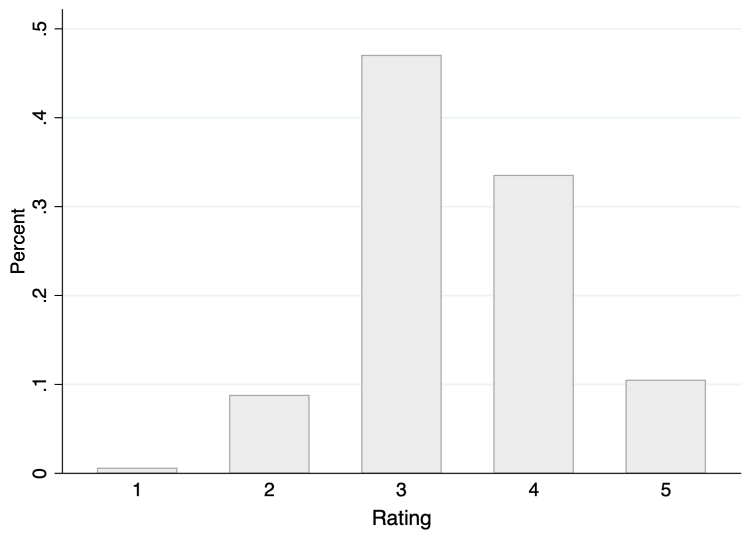
(b) Loss of Team Members



(c) Denial Rate

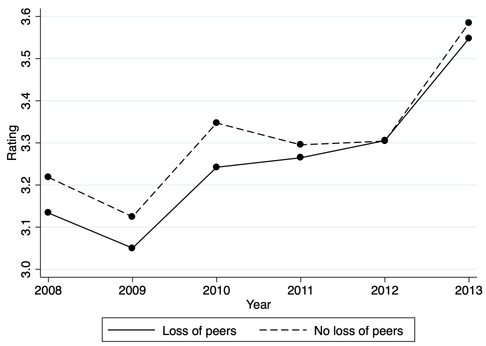
Notes: These figures plot the results of H-1B visa extensions by calendar year in our sample. Plot (a) presents the raw number of H1-B visa extensions approved and denied. Plot (b) shows the percentage of denied cases among the total number of team members (%), and plot (c) shows the percentage of denied cases among the total number of visa-extension applications (%).

Figure 2: DISTRIBUTION OF RATINGS AT THE INDIVIDUAL LEVEL

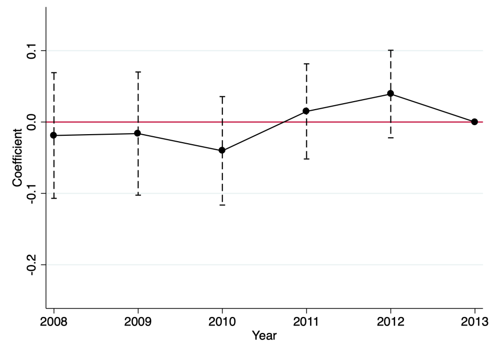


Note: This histogram presents the percentage of average employee ratings, by whole number.

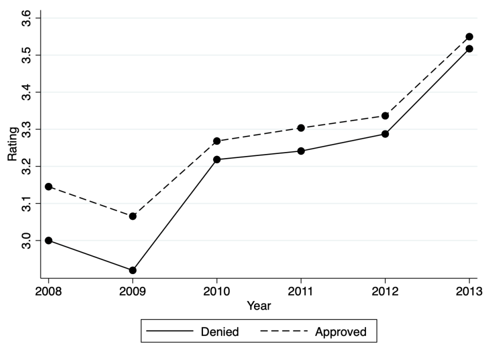
Figure 3: BASELINE INDIVIDUAL RATINGS BY STATUS, 2008–2013



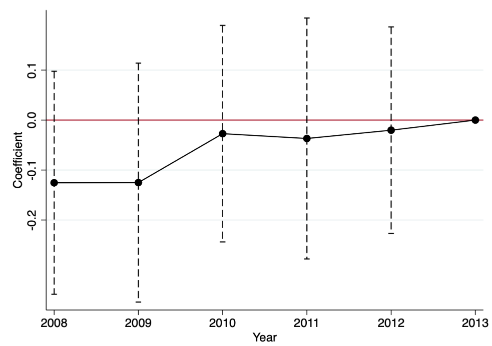
(a) Visa Status of Peers



(b) Visa Status of Peers, Coefficient



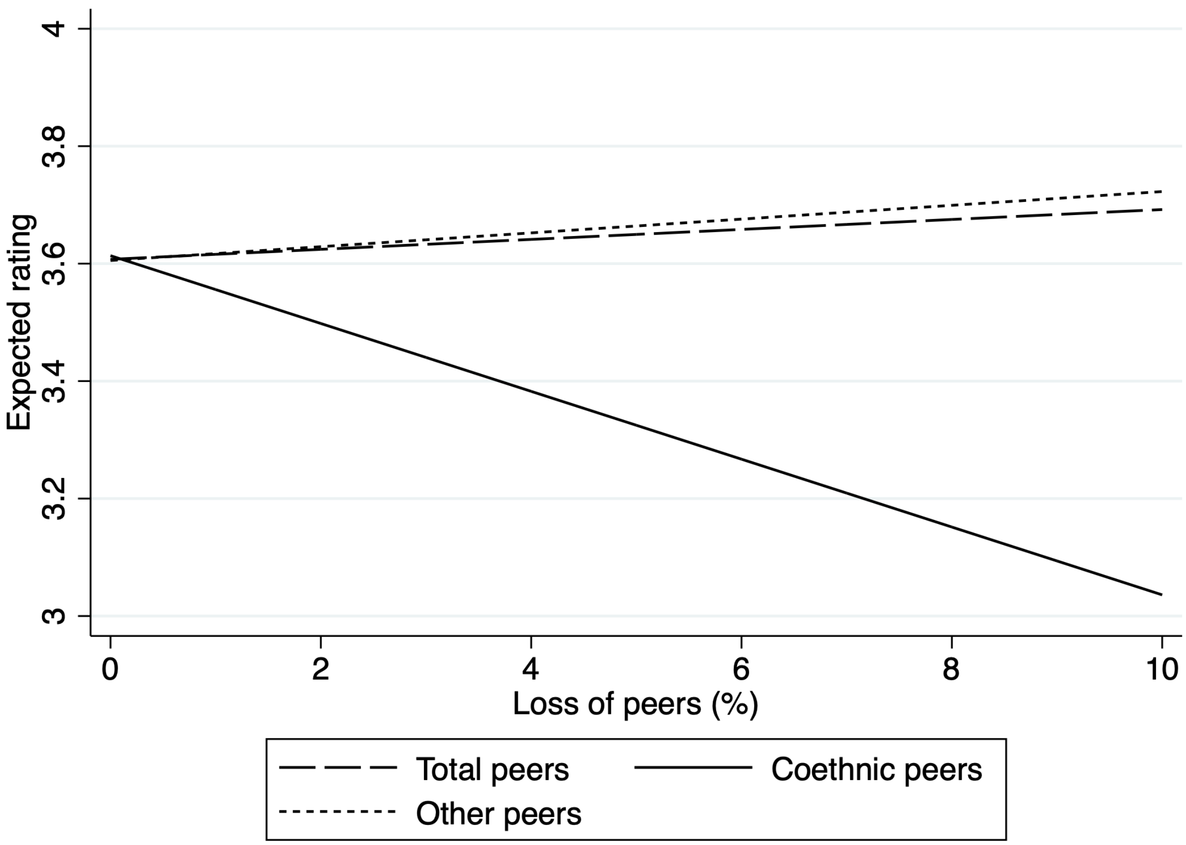
(c) Visa Status



(d) Visa Status, Coefficient

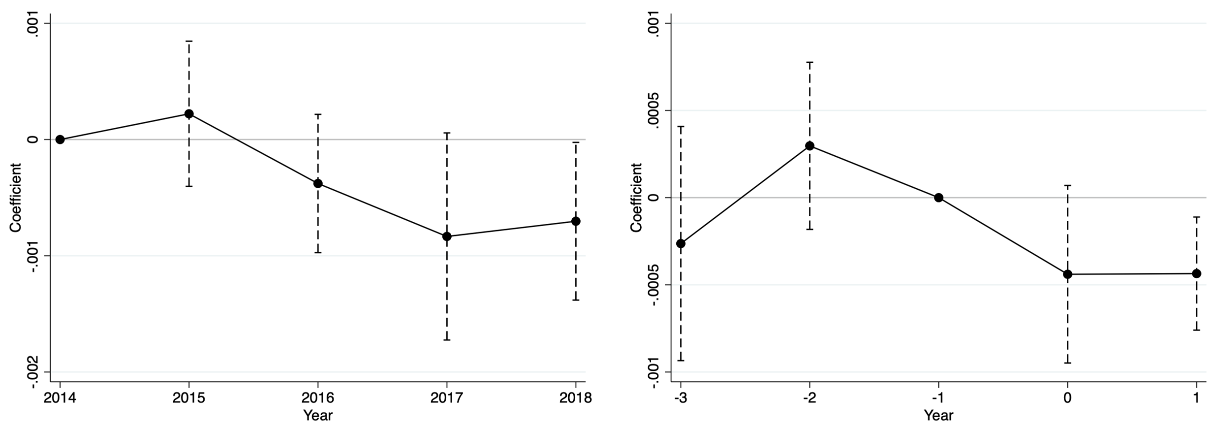
Notes: These figures present pretrends for our main outcome, i.e., individual annual performance ratings. Since H-1B visa extensions in our sample began to be filed and approved in 2014, we investigate pretrends between 2008 and 2013. Plot (a) shows the average annual rating of employees whose visa extension was neither denied nor filed. The solid line depicts the average rating of employees who have one or more team members whose visa extension was denied (loss of peers) while the dashed line shows the average rating of employees who did not lose a peer in their team (no loss of peer). Plot (b) presents the coefficient estimates of the regression in equation 3 (using 2013 as the base year) for the preperiod. Plots (c) and (d) compare the ratings of employees whose visa extension was denied versus employees whose visa extension was approved. Plot (c) shows raw data, while plot (d) shows coefficient estimates. In all plots we show 95% confidence intervals.

Figure 4: PREDICTED RATING



Notes: The figures show the expected ratings in response to the loss of peers. We use a balanced panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed (for the 2014–2018 period). Standard errors are clustered at the team level.

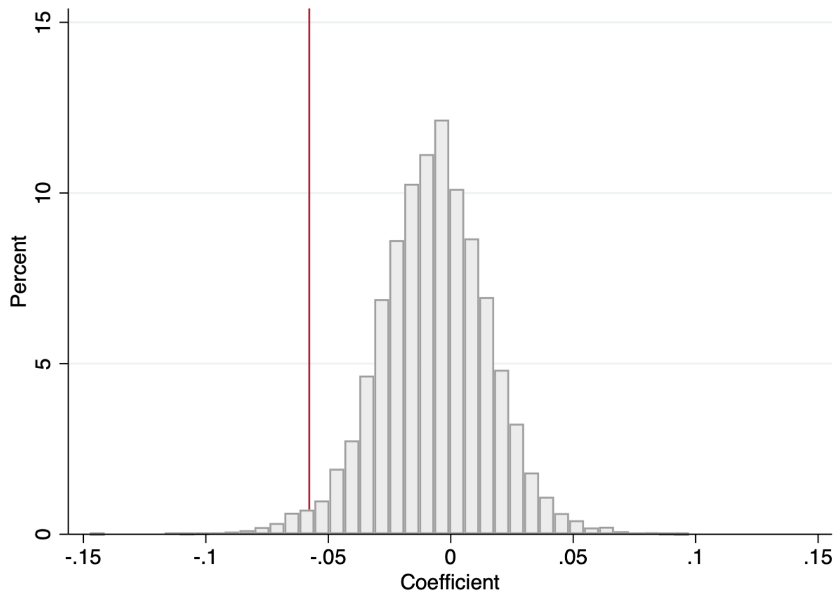
Figure 5: DIFFERENCE-IN-DIFFERENCES IN INDIVIDUAL RATINGS IN RESPONSE TO THE LOSS OF THE CO-ETHNIC PEERS



(a) Effect Relative to the Base Year 2014 (b) Effect Relative to a Year Before the Loss

Notes: Plot (a) shows regression coefficients on the loss of the same-ethnicity peers in equation 3 relative to the base year 2014. Plot (b) shows the coefficients relative to a year before the loss. We plot confidence intervals at the 95% level.

Figure 6: PLACEBO TEST



Notes: This figure plots the coefficient estimates of a placebo treatment test. There are 283 employees in our sample whose visa extension was denied. To perform this placebo test, we randomly choose 283 employees, without replacement, and construct the placebo treatment for the loss of the same-ethnicity peers assuming their visa extension is denied. We reestimate the regression in equation 3 and record the coefficient estimate with this new placebo treatment variable. We do this 10,000 times with different random shuffles. The figure shows the distribution of coefficient estimates of these 10,000 iterations. The solid vertical line depicts the actual causal effect using the true data. Finally, we calculate a p value by computing the proportion of the 10,000 iterations whose coefficient estimates were smaller than the actual coefficient estimate ($p < .001$).

Table 1: SUMMARY STATISTICS AT THE INDIVIDUAL LEVEL

	Mean (1)	Median (2)	SD (3)	Min. (4)	Max. (5)
Average rating	3.447	3	0.812	1	5
Rating					
1	0.005	0	0.070	0	1
2	0.087	0	0.282	0	1
3	0.469	0	0.499	0	1
4	0.335	0	0.472	0	1
5	0.104	0	0.306	0	1
H-1B visa extensions filed	0.441	0	0.497	0	1
Extensions denied if filed	0.138	0	0.345	0	1
Male	0.899	1	0.301	0	1
Birth year	1,981	1,981	5	1,956	1,991
PeerLoss (=Denials/Size %)	0.616	0	1.799	0	33.333
N team members (individual)	49	28	58	1	245
N team members (team)	8	2	18	1	245
N individuals	6,913				
N project teams	841				

Notes: Observations are at the employee-year level. The average rating is computed as the annual average employee rating between 2008 and 2018. The variable Rating presents the proportion of ratings as dummy variables for each rating, which can range from 1 to 5. The number of H-1B visa extension denials divided by the number of team members in percentage (PeerLoss) represents the treatment variable in our analysis using a panel data at the employee-year level. The average number of team members can be calculated at the individual level or at the project team level.

Table 2: NUMBER OF TEAMS THAT EXPERIENCE THE LOSS OF A MEMBER

Loss of Peers	Frequency	Percent
A. By loss of peers		
No	705	83.83
Yes	136	16.17
B. By number of lost peers		
0	705	83.83
1	75	8.92
2	33	3.92
3	11	1.31
4	6	0.71
5	4	0.48
6	2	0.24
9	2	0.24
11	2	0.24
13	1	0.12

Notes: The table shows the number of teams that experience the loss of a team member. Panel A considers the number of teams that experience the loss of at least one member, while Panel B shows a breakdown by the number of members lost.

Table 3: NUMBER OF INDIVIDUALS THAT EXPERIENCE THE LOSS OF A PEER

Loss of Peers (1)	Frequency (2)	Percent (3)
A. By loss of peers		
No loss of peers	2504	38.58
Loss of peers	3986	61.42
B. By number of lost peers		
0	2505	38.58
1	1284	19.78
2	929	14.31
3	492	7.58
4	260	4.00
5	185	2.85
6	106	1.63
9	200	3.08
11	378	5.82
13	154	2.37

Notes: The table shows the number of individuals that experience the loss of a team member. Panel A considers the number of teams that experience the loss of at least one member, while Panel B shows a breakdown by the number of members lost.

Table 4: NUMBER OF INDIVIDUALS WHO EXPERIENCE THE LOSS OF A CO-ETHNIC PEER

Panel A: By loss of co-ethnic peers

	No Loss of Co-Ethnic Peers	Loss of Co-Ethnic Peers	Total
No loss of peers	2504	0	2504
Loss of peers	1203	2783	3986
Total	3707	2783	6490

Panel B: By number of co-ethnic peers lost

		Loss of co-ethnic peer								
		0	**1**	**2**	**3**	**4**	**5**	**6**	**9**	**Total**
Loss of peers	**0**	2504	0	0	0	0	0	0	0	2504
	1	643	640	0	0	0	0	0	0	1283
	2	263	367	299	0	0	0	0	0	929
	3	166	96	124	106	0	0	0	0	492
	4	62	48	92	42	16	0	0	0	260
	5	28	13	55	48	0	40	0	0	184
	6	7	14	26	31	0	28	0	0	106
	9	8	11	51	0	14	38	78	0	200
	11	22	0	10	0	129	140	77	0	378
	13	4	0	50	0	0	0	0	100	154
	Total	3707	1189	707	227	159	246	155	100	6490

Notes: This table provides a breakdown of loss of peer by ethnicity (co-ethnic or non-co-ethnic). Panel A considers the number of individuals who experience the loss of at least one member by ethnicity. Panel B shows a breakdown outlining the number of lost peer by ethnicity.

Table 5: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS

Sample (Year)	Balanced (2014–2018)		Unbalanced (2008–2018)	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss	0.008**	0.012**	0.007*	0.011**
	(0.004)	(0.005)	(0.004)	(0.005)
PeerLoss	-	-0.058*	-	-0.072***
× Same ethnicity		(0.032)		(0.026)
Mean of outcome	3.610	3.610	3.436	3.436
Number of individuals	3,448	3,448	6,490	6,490
Number of units	430	430	835	835
Observations	17,240	17,240	42,389	42,389
R-squared	0.500	0.500	0.431	0.431

Notes: This table reports the coefficient estimates of the regression in equations 1 and 2 using the sample of employees whose H-1B visa extension was neither denied nor filed. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied (x 100). Columns 1 and 2 show the results for a balanced panel that has all employee ratings from 2014 and 2018 (our preferred specifications), while columns 3 and 4 use an unbalanced panel from 2008 and 2018, which contains some missing values for the outcome variable in some years. Columns 2 and 4 show the results for the loss of the same-ethnicity peers using the regression in equation 2. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 6: BASELINE INDIVIDUAL CHARACTERISTICS BY STATUS

	Means (SD)			Differences (SE)	
	Full sample	Loss of peers	No loss of peers	Columns 2–3	Controls
	(1)	(2)	(3)	(4)	(5)
Sample: Individuals whose visa extension is not denied (balanced panel)					
A. Status: Visa extension of peers is denied versus approved (level of unit: team)					
Rating, 2008–2013	3.293	3.265	3.377	-0.112***	0.019
	(0.684)	(0.685)	(0.676)	(0.017)	(0.025)
Male	0.925	0.919	0.941	-0.022	
	(0.264)	(0.273)	(0.236)	(0.016)	
Birth year	1978	1979	1978	1***	
	(4)	(4)	(4)	(0)	
N individuals	1,406	1,050	356	1,406	1,406
	Means (SD)			Differences (SE)	
	Full sample	Denied	Approved	Columns 2–3	Controls
Sample: Individuals who filed a visa extension (balanced panel)					
B. Status: Own visa extension is denied versus approved					
Rating, 2008–2013	3.270	3.197	3.278	-0.081**	-0.051
	(0.681)	(0.721)	(0.676)	(0.031)	(0.043)
Male	0.929	0.920	0.931	-0.011	
	(0.256)	(0.274)	(0.254)	(0.029)	
Birth year	1979	1979	1979	1	
	(4)	(5)	(4)	(0)	
N individuals	851	87	764	851	851

Notes: This table describes baseline characteristics of individuals between 2008 and 2013 before any H-1B visa extensions in our sample began to be filed and approved. In panel A, column 2 shows the means of variables for those who lost some team members due to H-1B visa-extension denials while column 3 presents the means of variables for those who did not lose any team members. Column 4 shows differences between the means of these two groups. Column 5 reports the coefficient estimates after controlling for individual characteristics such as gender and age. Panel B shows a similar comparison, taking into account individuals whose visa extension was denied versus individuals whose visa extension was approved. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 7: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING, IV ESTIMATES

Sample (Year)	Balanced (2014–2018)		Unbalanced (2008–2018)	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss (IV)	0.031	0.032**	0.042**	0.030**
	(0.021)	(0.013)	(0.021)	(0.014)
PeerLoss (IV)	–	-0.048*	–	-0.046*
× Same ethnicity		(0.025)		(0.026)
Mean of outcome	3.610	3.610	3.436	3.436
Number of individuals	3,448	3,448	6,490	6,490
Number of units	430	430	835	835
Observations	17,240	17,240	41,714	41,714
First-stage F test	32.810	23.810	37.580	25.504

Notes: This table reports the instrumented coefficient estimates of the regression in equations 1 and 2 using the sample of employees whose H-1B visa extension was neither denied nor filed. We instrument the treatment variable (percentage of team members whose visa extension was denied x100) with the percentage of team members whose H-1B visa extension was filed. The dependent variable is performance rating per year per person. Columns 1 and 2 show the results for a balanced panel that has all employee ratings from 2014 and 2018 while columns 3 and 4 use an unbalanced panel from 2008 and 2018, which contains missing values for the outcome variable in some years. Columns 2 and 4 show the results for the loss of the same-ethnicity peers. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 8: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS BY TYPE OF TASK

Sample	Atypical Tasks		Typical Tasks	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss	0.003	0.014*	0.007	0.009
	(0.006)	(0.008)	(0.004)	(0.006)
PeerLoss	-	-0.306**	-	-0.034
× Same ethnicity		(0.117)		(0.027)
Mean of outcome	3.572	3.572	3.612	3.612
Number of individuals	1,571	1,571	1,549	1,549
Number of units	151	151	209	209
Observations	7,855	7,855	7,745	7,745
R-squared	0.498	0.498	0.511	0.511

Notes: This table reports the coefficient estimates of the regressions shown in equations 1 and 2 using a balanced panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed (for the period 2014-2018). The sample is partitioned into two subsamples based on our measure of task uniqueness (build using a Jaccard similarity score on teams' names). We use the median value of the score as a threshold to split our sample. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied (x 100) ($PeerLoss$). Column 2 shows the results for the loss of the same-ethnicity peers using the regression in equation 2. Standard errors are clustered at the team level ($p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 9: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING BY POSITION

Position	Junior		Senior	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
Loss of juniors (%)	0.009	0.018**	0.020***	0.006
	(0.006)	(0.009)	(0.007)	(0.009)
Loss of seniors (%)	0.005	0.026*	0.003	0.001
	(0.008)	(0.014)	(0.007)	(0.008)
Loss of juniors (%)		-0.017*		0.035
× Same ethnicity		(0.009)		(0.022)
Loss of seniors (%)		-0.040*		0.005
× Same ethnicity		(0.024)		(0.012)
Mean of outcome	3.599	3.599	3.637	3.637
Number of teams	273	273	343	343
Observations	9,640	9,640	6,935	6,935

Notes: This table reports the coefficient estimates of the regressions shown in equations 1 and 2 using a balanced panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed (for the 2014–2018 period). The sample is partitioned into two subsamples based on position. We consider entry-level employees and software engineers as juniors, and team leaders and above as seniors. The dependent variable is performance rating per year per person. The treatment variable is the percentage of junior ($LossofJuniors(\%)$) or senior ($LossofSeniors(\%)$) team members whose H-1B visa extension was denied (x 100). Columns 2 and 4 show the results for the loss of the same-ethnicity peers using the regression in equation 2. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 10: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS BY TEAM SIZE

Sample	Small team		Large team	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss	0.010**	0.015***	0.001	-0.005
	(0.004)	(0.005)	(0.007)	(0.010)
PeerLoss × Same ethnicity	–	-0.072**	–	0.238
		(0.032)		(0.283)
Mean of outcome	3.679	3.679	3.535	3.535
Number of individuals	1,601	1,601	1,847	1,847
Number of units	372	372	58	58
Observations	8,005	8,005	9,235	9,235
R-squared	0.480	0.480	0.511	0.511
Team members	1-28		29-245	

Notes: This table reports the coefficient estimates of the regressions shown in equations 1 and 2 using a balanced panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed (for the period 2014-2018). The sample is partitioned into two subsamples based on team size, using the median value as a threshold (28 members). The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied (x 100) ($PeerLoss$). Column 2 shows the results for the loss of the same-ethnicity peers using the regression in equation 2. Standard errors are clustered at the team level ($p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 11: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS BY ETHNIC DIVERSITY

Sample	Low initial diversity		High initial diversity	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss	0.012***	0.017***	0.001	0.004
	(0.004)	(0.005)	(0.006)	(0.008)
PeerLoss	–	-0.069***	–	-0.103
× Same ethnicity		(0.024)		(0.101)
Mean of outcome	3.611	3.611	3.608	3.608
Number of individuals	1,832	1,832	1,821	1,821
Number of units	327	327	110	110
Observations	8,659	8,659	8,408	8,408
R-squared	0.511	0.511	0.494	0.494

Notes: This table reports the coefficient estimates of the regressions shown in equations 1 and 2 using a balanced panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed (for the period 2014-2018). The sample is partitioned into two subsamples based on team ethnic diversity, using the median value of the ethnolinguistic fractionalization (ELF) measure as a threshold. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied (x 100) ($PeerLoss$). Column 2 shows the results for the loss of the same-ethnicity peers using the regression in equation 2. Standard errors are clustered at the team level ($p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 12: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING BY AGE

Sample	Young		Old	
	(1)	(2)	(3)	(4)
A. Outcome: Individual ratings of team members				
PeerLoss	0.009*	0.012**	0.006	0.010
	(0.005)	(0.006)	(0.008)	(0.011)
PeerLoss × Same ethnicity	-	-0.050	-	-0.072
		(0.033)		(0.087)
Mean of outcome	3.554	3.554	3.665	3.665
Number of individuals	2,377	2,377	2,214	2,214
Number of units	390	390	344	344
Observations	8,953	8,953	8,287	8,287
R-squared	0.555	0.555	0.539	0.539

Notes: This table reports the coefficient estimates of the regressions shown in equations 1 and 2 using a balanced panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed (for the 2014–2018 period). The sample is partitioned into two subsamples based on age. We use the median value as a threshold to split our sample and we define young employees as individuals who would not be more than 33 years old at the start of our period (i.e., 2014). The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied (x 100) ($PeerLoss$). Column 2 shows the results for the loss of the same-ethnicity peers using the regression in equation 2. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 13: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING BY GENDER

Sample	Male		Female	
	(1)	(2)	(3)	(4)
A. Outcome: Individual ratings of team members				
PeerLoss	0.009**	0.012**	0.005	0.018
	(0.004)	(0.005)	(0.013)	(0.015)
PeerLoss × Same ethnicity	-	-0.054*	-	-0.446
		(0.031)		(0.297)
Mean of outcome	3.621	3.621	3.486	3.486
Number of individuals	3,147	3,147	301	301
Number of units	416	416	144	144
Observations	15,735	15,735	1,505	1,505
R-squared	0.503	0.503	0.459	0.460

Notes: This table reports the coefficient estimates of the regressions shown in equations 1 and 2 using a balanced panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed (for the 2014–2018 period). The sample is partitioned into two subsamples based on gender. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied (x 100) ($PeerLoss$). Column 2 shows the results for the loss of the same-ethnicity peers using the regression in equation 2. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 14: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING BY SALARY

Sample	Low salary		High salary	
	(1)	(2)	(3)	(4)
A. Outcome: Individual ratings of team members				
PeerLoss	0.010*	0.014**	0.008	0.011*
	(0.005)	(0.007)	(0.005)	(0.006)
PeerLoss × Same ethnicity	-	-0.068*	-	-0.055
		(0.037)		(0.053)
Mean of outcome	3.631	3.631	3.596	3.596
Number of individuals	1,603	1,603	1,707	1,707
Number of units	270	270	367	367
Observations	8,015	8,015	8,535	8,535
R-squared	0.509	0.509	0.490	0.490

Notes: This table reports the coefficient estimates of the regressions shown in equations 1 and 2 using a balanced panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed (for the 2014–2018 period). The sample is partitioned into two subsamples based on salary, split along the median value ($91,861). The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied (x 100) ($PeerLoss$). Column 2 shows the results for the loss of the same-ethnicity peers using the regression in equation 2. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

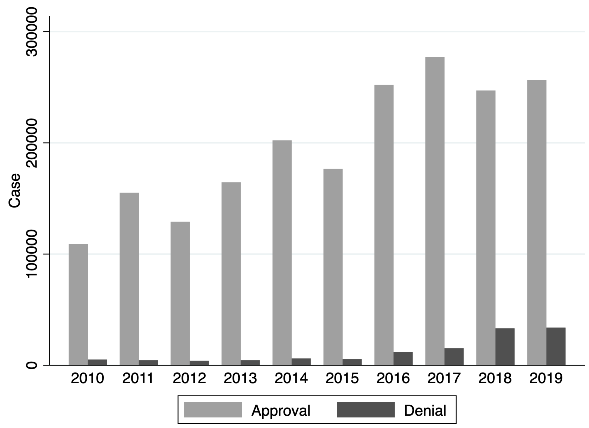
Table 15: EFFECT OF LOSING TEAM MEMBERS AND THE QUALITY OF PEERS

Sample (Year)	Balanced (2014–2018)	
	(1)	(2)
A. Outcome: Individual ratings of team members		
Loss of High-performance peer	0.005	0.011
	(0.006)	(0.007)
Loss of Low-performance peer	0.011*	0.014**
	(0.006)	(0.007)
Loss of High-performance peer × Same ethnicity	–	-0.138*
		(0.075)
Loss of Low-performance peer × Same ethnicity	–	-0.040
		(0.026)
Mean of outcome	3.610	3.610
Number of individuals	3,448	3,448
Number of units	430	430
Observations	17,240	17,240
R-squared	0.500	0.500

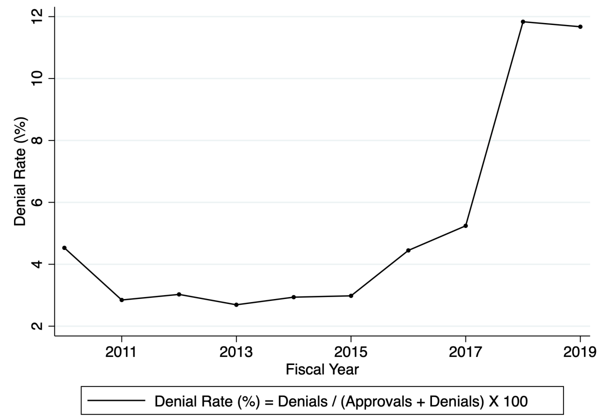
Notes: This table reports the coefficient estimates of the regressions shown in equations 1 and 2 using a balanced panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed (for the 2014–2018 period). A high-performance peer is defined as a team member whose average rating is higher than the rating assigned to her team. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied (x 100) ($PeerLoss$). Column 2 shows the results for the loss of the same-ethnicity peers using the regression in equation 2. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Appendix Figures and Tables

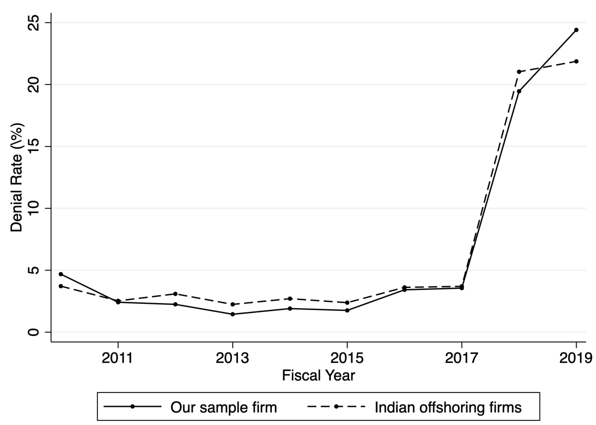
Figure A.1: H-1B VISA EXTENSION APPROVALS AND DENIALS FROM ADMINISTRATIVE DATA (FISCAL YEARS)



(a) Visa-Extension Approvals and denials (all firms)



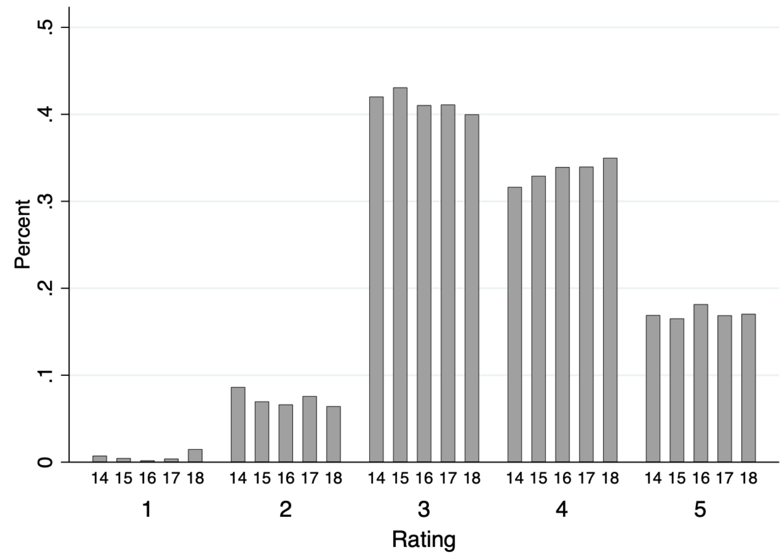
(b) Visa-Extension Denial Rate (all firms)



(c) Visa-Extension Denial Rate (sample firm vs. Indian offshoring firms)

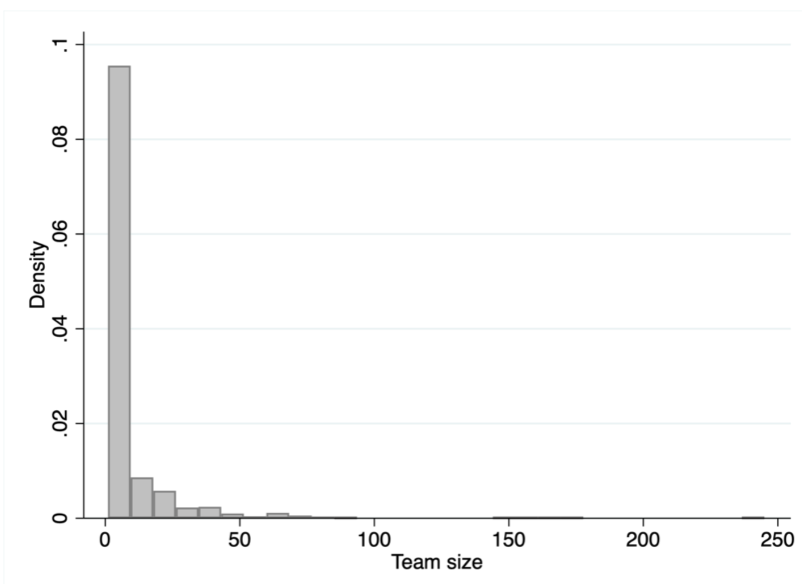
Notes: Figures (a) and (b) presents data about all petitions filed with USCIS requesting an extension of existing H-1B visas (primarily for existing employees at the same company) from the USCIS H-1B Employer Data Hub. These data include all the visas extensions filed in the United States, for all employers. Plot (a) presents the number of H-1B visa extensions approved or denied by fiscal year. Plot (b) shows denial rates in percentage by year. Figure (c) shows denial rates in percentage by fiscal year for our sample firm vs. all Indian offshoring firms.

Figure A.2: DISTRIBUTION OF RATINGS AT THE INDIVIDUAL LEVEL BY YEAR



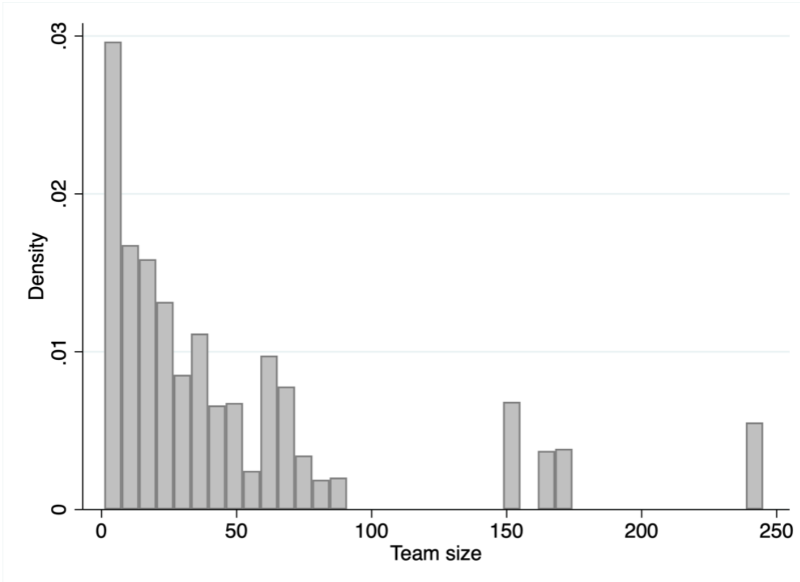
Notes: This histogram presents the percentage of average employee ratings, by whole number by year.

Figure A.3: HISTOGRAM OF TEAM SIZE (TEAM LEVEL)



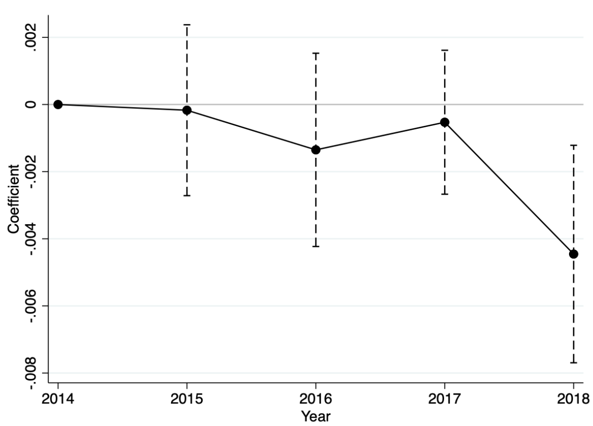
Notes: This histogram presents the distribution of team size at the team level.

Figure A.4: HISTOGRAM OF TEAM SIZE (INDIVIDUAL LEVEL)

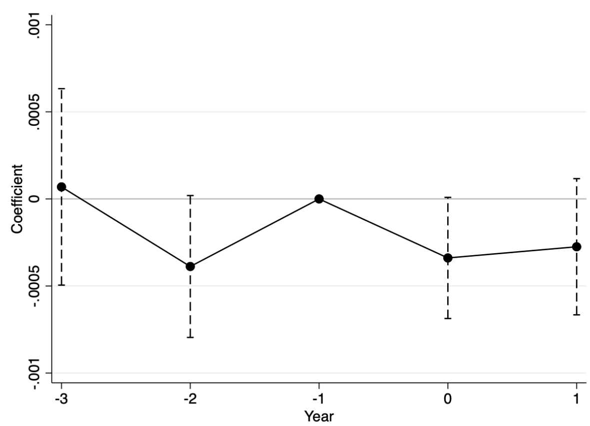


Notes: This histogram presents the distribution of team size at the individual level.

Figure A.5: DIFFERENCE-IN-DIFFERENCES IN INDIVIDUAL RATINGS IN RESPONSE TO THE LOSS OF THE SAME-ETHNICITY PEERS (BUSINESS UNIT)



(a) Effect Relative to the Base Year 2014

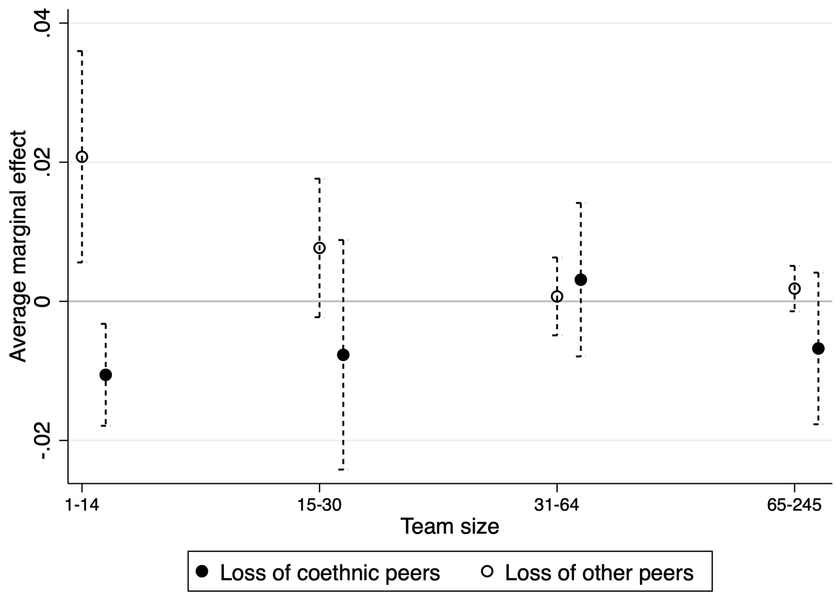


(b) Effect Relative to a Year Before the Loss

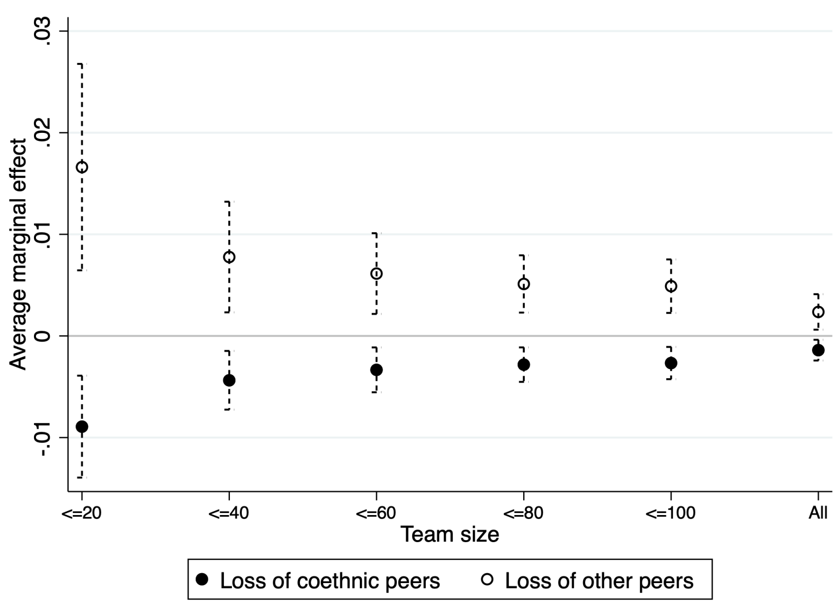
Notes: Plot (a) shows the regression coefficients on the loss of the same-ethnic peers ($LossPeer$) at the business-unit level, included in equation 3, relative to the base year 2014. Plot (b) shows coefficients relative to a year before the loss. In both plots, we used a balanced panel that includes all employees' ratings from 2014 and 2018 and we show 95% confidence intervals.

Figure A.6: AVERAGE MARGINAL EFFECT BY TEAM SIZE

(a) Team size (four subgroups)



(b) Maximum team size



Notes: The figures shows the average marginal effect by team size and maximum team size (i.e., the average marginal effects on increasingly bigger groups). The average marginal effects present the coefficient estimates of the regression considering the average loss of peers with 95% confidence intervals. We use a balanced panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed (for the 2014–2018 period). Standard errors are clustered at the team level.

Table A.1: ETHNIC CLASSIFICATION

Native State (1)	Geographic Classification (2)	Linguistic Classification (3)	Percentage (%) (4)
Andhra Pradesh	South India	Telegu	10.07
Assam	Northeast India	Assamese	0.09
Bihar	North India	Hindi	2.36
Chhattisgarh	North India	Hindi	0.09
Goa	West India	Goanese	0.18
Gujarat	West India	Gujarati	1.29
Haryana	North India	Hindi	0.99
Himachal Pradesh	North India	Hindi	0.12
Jammu And Kashmir	North India	Kashmiri	0.56
Jharkhand	North India	Hindi	0.65
Karnataka	South India	Kannad	5.09
Kerala	South India	Malayali	5.34
Madhya Pradesh	North India	Hindi	3.17
Maharashtra	West India	Marathi	4.01
Delhi	North India	Hindi	1.94
Odisha	East India	Oriya	1.29
Puducherry	South India	Tamil	0.23
Punjab	North India	Punjabi	6.45
Rajasthan	North India	Hindi	4.83
Sikkim	East India	Sikkimese	0.08
Tamil Nadu	South India	Tamil	30.70
Telangana	South India	Telegu	0.34
Tripura	Northeast India	Bengali	0.01
Uttar Pradesh	North India	Hindi	17.73
Uttarakhand	North India	Hindi	0.41
West Bengal	East India	Bengali	2.00

Table A.2: DISTRIBUTION OF ETHNICITY

Ethnicity	Employee (1)	Project team (2)	Business unit (3)
East India	0.033	0.033	0.049
North India	0.398	0.423	0.437
South India	0.515	0.488	0.453
West India	0.053	0.055	0.067
North Eastern India	0.001	0.000	0.000
Observations	6,910	840	186

Notes: The table presents the proportion of ethnicity in Column 1 at the individual level, and the average proportion of ethnicity in Column 2 at the project team level and at the business unit level in Column 3.

Table A.3: BASELINE INDIVIDUAL CHARACTERISTICS BY STATUS

	Means (SD)			Differences (SE)
	Full sample	Visa Denied	Visa Approved	Columns 2-3
	(1)	(2)	(3)	(4)
Male	0.929	0.920	0.931	-0.011
	(0.256)	(0.274)	(0.254)	(0.029)
Birth year	1978.580	1979.069	1978.525	0.544
	(4.172)	(4.523)	(4.129)	(0.472)
Major ethnicity	0.580	0.586	0.580	0.006
	(0.494)	(0.495)	(0.494)	(0.056)
Higher position	0.684	0.632	0.690	-0.058
	(0.465)	(0.485)	(0.463)	(0.053)
Team size	62.094	56.057	62.781	-6.724
	(61.002)	(55.315)	(61.612)	(6.903)
N individuals	851	87	764	851

Notes: The table describes baseline characteristics of individuals who filed a visa extension. Column 2 shows means of variables of individuals whose H-1B visa extension was denied while column 3 presents those whose visa extension was approved. Column 4 shows differences and standard errors (in parentheses).

Table A.4: EFFECT OF PEER LOSS ON INDIVIDUAL RATINGS (DUMMY TREATMENT)

Sample	All		Small teams	Large teams
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss	0.046	0.078	0.172	0.040
	(0.023)**	(0.030)***	(0.050)***	(0.039)
	[0.019]**	[0.026]***	[0.053]***	[0.032]
PeerLoss ×		-0.054	-0.121	-0.039
Same ethnicity		(0.034)	(0.062)**	(0.038)
		[0.029]*	[0.066]*	[0.032]
Observations	41,714	41,714	20,093	21,621

Notes: This table reports the coefficient estimates of the regressions shown in equations 1 and 2 in the paper using a panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed. The dependent variable is performance rating per year per person. The treatment variable is a dummy indicating the loss of at least one peer and it is measured as the percentage of team members with denials X 100. Column 2 shows the results for the loss of the same-ethnicity peers using the regression in equation 2. Columns 3 and 4 shows the results from the same specification in Column 2, while splitting the sample depending on team size. Standard errors clustered at the team level are reported in brackets, while standard errors clustered at the individual level are reported in squared brackets: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.5: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS: ALTERNATIVE AGGREGATION LEVELS FOR THE TREATMENT VARIABLE

Sample (Year)	Balanced (2014–2018)		Unbalanced (2008–2018)	
	(1)	(2)	(3)	(4)
Individual ratings of members by business unit				
PeerLoss	0.001	0.010	-0.001	0.005
	(0.013)	(0.013)	(0.013)	(0.014)
PeerLoss × Same ethnicity	-	-0.351**	-	-0.254**
		(0.163)		(0.106)
Mean of outcome	3.622	3.622	3.423	3.423
Number of individuals	3,448	3,448	6,490	6,490
Number of units	90	90	187	187
Observations	17,240	17,240	42,389	42,389
R-squared	0.499	0.499	0.430	0.431

Notes: This table reports the coefficient estimates of the regression in equations 1 and 2 using the sample of employees whose H-1B visa extension was neither denied nor filed. The treatment variable is the percentage of team members whose H-1B visa extension was denied (x 100) ($PeerLoss$) at the business-unit level. Columns 1 and 2 show the results for a balanced panel that has all employee ratings from 2014 and 2018 while columns 3 and 4 use an unbalanced panel from 2008 and 2018 that contains some missing values for our outcome variable in some years. Columns 2 and 4 show the results for the loss of the same-ethnicity peers using the regression in equation 2. Standard errors are clustered at the team level in panel A and at the business-unit level in panel B. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A.6: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING, ORDERED LOGIT ESTIMATES

Sample (Year)	Balanced (2014–2018)		Unbalanced (2008–2018)	
	(1)	(2)	(3)	(4)
A. Outcome: Individual ratings of team members				
PeerLoss	0.017	0.025**	0.016	0.026**
	(0.010)	(0.013)	(0.011)	(0.013)
PeerLoss × Same ethnicity	-	-0.148**	-	-0.133**
		(0.073)		(0.053)
Mean of outcome	3.610	3.610	3.436	3.436
Number of individuals	3,448	3,448	6,490	6,490
Number of units	430	430	835	835
Observations	17,240	17,240	42,389	42,389
R-squared	157.174	161.732	1577.339	1589.133

Notes: This table reports the ordered logit estimates using the sample of employees whose H-1B visa extension was neither denied nor filed. The dependent variable is performance rating per year per person, in an ordered index that ranges from 1 to 5. The treatment variable is the percentage of team members whose H-1B visa extension was denied (x 100) ($PeerLoss$) at the team level. Columns 1 and 2 show the results for a balanced panel that has all employee ratings from 2014 and 2018 while columns 3 and 4 use an unbalanced panel from 2008 and 2018 that contains some missing values for our outcome variable in some years. Columns 2 and 4 show the results for the loss of the same-ethnicity peers. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A.7: PLACEBO TEST: EFFECT OF LOSING TEAM MEMBERS AND OTHER ETHNICITY ON INDIVIDUAL RATINGS

Sample (Year)	Balanced (2014–2018)		Unbalanced (2008–2018)	
	(1)	(2)	(3)	(4)
A. Outcome: Individual ratings of team members				
PeerLoss	0.008**	0.009*	0.007*	0.006
	(0.004)	(0.005)	(0.004)	(0.005)
PeerLoss	-	-0.008	-	0.027
× Other ethnicity		(0.042)		(0.041)
Mean of outcome	3.610	3.610	3.436	3.436
Number of individuals	3,448	3,448	6,490	6,490
Number of units	430	430	835	835
Observations	17,240	17,240	42,389	42,389
R-squared	0.500	0.500	0.431	0.431

Notes: This table reports the coefficient estimates of the regression for a placebo test that exploits the loss of the other-ethnicity peers. We consider the sample of employees whose H-1B visa extension was neither denied nor filed. Columns 2 and 4 show the results for the loss of the other-ethnicity peers using the regression in equation 2. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied (x 100) ($PeerLoss$) at the team level. Columns 1 and 2 show the results for a balanced panel that has all employee ratings from 2014 and 2018 while columns 3 and 4 use an unbalanced panel from 2008 and 2018. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A.8: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS EXCLUDING SOME GROUPS

Sample	Tamil Nadu & Uttar Pradesh Excluded (1)	Tamil Nadu Excluded (2)	Uttar Pradesh Excluded (3)	Only Tamil Nadu & Uttar Pradesh (4)
Outcome: Individual ratings of team members				
PeerLoss	0.009	0.011**	0.010*	0.014**
	(0.006)	(0.005)	(0.005)	(0.006)
PeerLoss	-0.079*	-0.068**	-0.079***	-0.067*
× Same ethnicity	(0.041)	(0.032)	(0.029)	(0.039)
Mean of outcome	3.423	3.439	3.425	3.448
Number of individuals	3,365	4,518	5,340	3,128
Number of units	645	727	768	606
Observations	21,639	28,663	34,690	20,075
R-squared	0.417	0.417	0.411	0.408

Notes: The table reports the coefficient estimates of the regression in equations 1 and 2 using the sample of employees whose H-1B visa extension was neither denied nor filed. The dependent variable is rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied. Column 1 exclude employees from Tamil Nadu and Uttar Pradesh, and columns 2 and 3 do not include employees from Tamil Nadu and Uttar Pradesh, respectively. Column 4 only include employees from Tamil Nadu and Uttar Pradesh. Standard errors are clustered at team level. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.9: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING (LINGUISTIC CLASSIFICATION)

Sample (Year)	Balanced (2014–2018)		Unbalanced (2008–2018)	
	(1)	(2)	(3)	(4)
A. Outcome: Individual ratings of team members				
PeerLoss	0.008**	0.009**	0.007*	0.009*
	(0.004)	(0.004)	(0.004)	(0.004)
PeerLoss	-	-0.029	-	-0.048*
× Same ethnicity		(0.026)		(0.026)
Mean of outcome	3.610	3.610	3.436	3.436
Number of individuals	3,448	3,448	6,490	6,490
Number of units	430	430	835	835
Observations	17,240	17,240	42,389	42,389
R-squared	0.500	0.500	0.431	0.431

Notes: This table reports the coefficient estimates of the regression in equations 1 and 2 using the sample of employees whose H-1B visa extension was neither denied nor filed. In this robustness check, we use a linguistic classification instead of state of birth to identify employees of the same ethnic groups. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied (x 100) ($PeerLoss$) at the team level. Columns 1 and 2 show the results for a balanced panel that includes all employee ratings from 2014 and 2018 while columns 3 and 4 use an unbalanced panel from 2008 and 2018 that contains some missing values for our outcome variable in some years. Columns 2 and 4 show the results for the loss of the same-ethnicity peers using the regression in equation 2. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A.10: EFFECT OF LOSING TEAM MEMBERS ON INDIVIDUAL RATING BY THE TYPE OF TEAM MEMBER

	Ethnicity (1)	Gender (2)	Age group (3)	Homophily (4)
Outcome: Individual ratings of team members				
PeerLoss	0.012***	0.019**	0.006	0.017*
	(0.004)	(0.009)	(0.005)	(0.010)
PeerLoss	-0.058**			-0.061**
× Same ethnicity	(0.029)			(0.030)
PeerLoss		-0.012		-0.010
× Same gender		(0.010)		(0.010)
PeerLoss			0.004	0.006
× Same age group			(0.007)	(0.007)
Mean of outcome	3.613	3.613	3.613	3.613
Number of teams	430	430	430	430
Observations	17,240	17,240	17,240	17,240

Notes: This table reports the coefficient estimates of the regression in equation 2 using a balanced panel that includes all employees whose H-1B visa extension was neither denied nor filed in the 2014–2018 period. The dependent variable is performance rating per year per person. $PeerLoss$, our treatment variable, is defined as the percentage of team members whose H-1B visa extension was denied at the team level (x 100). The table shows the effects of the loss of team members from the same ethnicity, gender, or age group on peer performance. Comparing these three coefficients, we find that they statistically differ ($p = 0.065$). Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A.11: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING WITH ADDITIONAL CONTROLS

Sample (Year)	Balanced (2014-2018)		Unbalanced (2008-2018)	
	(1)	(2)	(3)	(4)
A. Outcome: Individual ratings of team members				
PeerLoss	0.008**	0.012**	0.006	0.010*
	(0.004)	(0.005)	(0.004)	(0.005)
PeerLoss	-	-0.055*	-	-0.059**
× Same ethnicity		(0.032)		(0.028)
Mean of outcome	3.610	3.610	3.436	3.436
Number of individuals	3,448	3,448	6,490	6,490
Number of units	430	430	835	835
Observations	17,240	17,240	42,389	42,389
R-squared	0.500	0.500	0.431	0.431

Notes: This table reports the coefficient estimates of the regression in equations 1 and 2 using the sample of employees whose H-1B visa extension was neither denied nor filed. We include additional variables in the regression that control for potential confounding effects of ethnic diversity. Specifically, we include two time-varying controls: the proportion of same-ethnicity peers in the team, and the ethnolinguistic fractionalization (ELF) measure, which is computed as one minus the Herfindahl index of ethnic group shares. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied ($PeerLoss$) at the team level (x 100). Columns 1 and 2 show the results for a balanced panel that includes all employee ratings from 2014 to 2018 while columns 3 and 4 use an unbalanced panel from 2008 and 2018 that contains some missing values for our outcome variable in some years. Columns 2 and 4 show the results for the loss of the same-ethnicity peers using the regression in equation 2. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A.12: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON TURNOVER

Sample (Year)	Unbalanced (2014–2018)	
	(1)	(2)
A. Outcome: Turnover within teams		
PeerLoss	-0.001	-0.001
	(0.001)	(0.002)
PeerLoss × Same ethnicity	-	0.006
		(0.009)
Mean of outcome	0.095	0.095
Number of individuals	6,431	6,431
Number of units	812	812
Observations	27,134	27,134
R-squared	0.436	0.436
B. Turnover within business units		
PeerLoss	-0.001	-0.003
	(0.004)	(0.003)
PeerLoss × Same ethnicity	-	0.078
		(0.108)
Mean of outcome	0.095	0.095
Number of individuals	6,431	6,431
Number of units	181	181
Observations	27,134	27,134
R-squared	0.436	0.436

Notes: This table reports the coefficient estimates of the regression in equations 1 and 2, but we consider turnover as the main dependent variable. This measure is a dummy variable that becomes equal to one when an employee leaves the team in a given year. The treatment variable is the percentage of team members whose H-1B visa extension was denied at the team level (x 100) ($PeerLoss$). Column 2 shows the results for the loss of same-ethnicity peers using the regression in equation 2. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A.13: DENIAL RATES BY ETHNIC CLASSIFICATION

Geographic Classification			Linguistic Classification		
(1)			(2)		
Outcome: Visa extension was denied or not					
Assam	-0.033	(0.081)	Bengali	0.044	(0.083)
Bihar	0.030*	(0.017)	Goanese	-0.000	(0.099)
Chhattisgarh	0.110	(0.075)	Gujarati	0.012	(0.084)
Delhi	0.003	(0.018)	Hindi	0.042	(0.081)
Goa	-0.033	(0.058)	Kannad	0.042	(0.082)
Gujarat	-0.021	(0.023)	Kashmiri	-0.000	(0.087)
Haryana	-0.005	(0.025)	Malayali	0.043	(0.082)
Himachal Pradesh	-0.033	(0.067)	Marathi	0.048	(0.082)
Jammu and Kashmir	-0.033	(0.033)	Oriya	0.057	(0.084)
Jharkhand	0.029	(0.030)	Punjabi	0.042	(0.081)
Karnataka	0.009	(0.013)	Sikkimese	-0.000	(0.120)
Kerala	0.010	(0.013)	Tamil	0.042	(0.081)
Madhya Pradesh	-0.006	(0.015)	Telegu	0.034	(0.081)
Maharashtra	0.015	(0.014)			
Odisha	0.024	(0.022)			
Puducherry	0.029	(0.050)			
Punjab	0.008	(0.012)			
Rajasthan	0.014	(0.013)			
Sikkim	-0.033	(0.089)			
Tamil Nadu	0.009	(0.009)			
Telangana	0.012	(0.043)			
Tripura	-0.033	(0.199)			
Uttar Pradesh	0.007	(0.009)			
Uttarakhand	0.036	(0.038)			
West Bengal	0.012	(0.019)			
F statistics	0.555		0.501		
p-value	0.964		0.925		
Observations	6,910		6,910		

Notes: This table shows the results of two regressions where ethnicity is regressed on denial rates. In Column (1) a geographic classification is used, while in Column (2) a linguistic one is used. The omitted category in Column 1 is Andhra Pradesh while the omitted category in Column (2) is Assamese. The final F-stat and p-value refer to a test of equality of coefficients.

Table A.14: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS BY VISA EXTENSION STATUS

Sample (Year)	Balanced (2014-2018)		Unbalanced (2008-2018)	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss	0.006	0.010**	0.006	0.009*
	(0.004)	(0.005)	(0.004)	(0.005)
PeerLoss	-	-0.073***	-	-0.054**
× Same ethnicity		(0.023)		(0.026)
Mean of outcome	3.455	3.455	3.418	3.418
Number of individuals	5,033	5,033	5,715	5,715
Number of units	782	782	792	792
Observations	25,346	25,340	34,933	34,927
R-squared	0.463	0.464	0.412	0.412

Notes: We use the sample of employees whose H-1B visa extension was filed. Standard errors are clustered at project teams. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.15: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS WITH STATE-LEVEL CONTROLS

Sample (Year)	Balanced (2014-2018)		Unbalanced (2008-2018)	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss	0.008**	0.011***	0.007*	0.011**
	(0.004)	(0.004)	(0.004)	(0.005)
PeerLoss	-	-0.056**	-	-0.071***
× Same ethnicity		(0.029)		(0.024)
Mean of outcome	3.610	3.610	3.435	3.435
Number of individuals	3,448	3,448	6,493	6,493
Number of units	430	430	836	836
Observations	17,240	17,240	41,714	41,714
R-squared	0.500	0.500	0.413	0.413

Notes: The table reports the coefficient estimates of the regression in equations 1 and 2 using the sample of employees whose H-1B visa extension was neither denied nor filed. We include their state of birth characteristics (log of population, log of GDP, workers %, literates %, graduates %, technical degree %, Hindu %, and Muslim %) from 2011 Census of India. Controls are interacted with year trends. The dependent variable is rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied. Columns 1 and 2 show the results for balanced panel that includes all employees' ratings from 2014 and 2018 while columns 3 and 4 use an unbalanced panel from 2008 and 2018, which contains some missing values for the outcome variable in some years. Columns 2 and 4 show the results for the loss of the same-ethnic peers using the regression in equation 2. Standard errors are clustered at team level. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.16: THE EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING BY THE TYPE OF TASKS AND POSITION

Type of tasks	Atypical tasks		Typical tasks	
Position	Junior (1)	Senior (2)	Junior (3)	Senior (4)
Outcome: Individual ratings of team members				
Loss of Juniors (%)	0.011 (0.020)	-0.002 (0.015)	0.020** (0.009)	0.026** (0.013)
Loss of Seniors (%)	0.042** (0.017)	-0.016 (0.020)	0.008 (0.019)	-0.010 (0.009)
Loss of Juniors (%) × Same ethnicity	-0.026 (0.023)	0.050* (0.028)	-0.016* (0.010)	-0.003 (0.021)
Loss of Seniors (%) × Same ethnicity	-0.097*** (0.029)	0.016 (0.023)	-0.017 (0.028)	-0.001 (0.014)
Mean of outcome	3.410	3.459	3.424	3.483
Number of teams	206	219	212	246
Observations	11,634	5,498	12,506	6,557

Notes: This table reports the coefficient estimates of the regressions shown in equations 1 and 2. The sample is partitioned into four subsamples based on task type and position. The dependent variable is performance rating per year per person. The treatment variable is the percentage of junior (LossofJuniors(%)) or senior (LossofSeniors(%)) team members whose H-1B visa extension was denied. Standard errors are clustered at the team level ($p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A.17: FREQUENCY OF THE LOSS OF CO-ETHNIC PEERS FOR INDIVIDUALS IN SMALL AND LARGE TEAMS

	No loss of co-ethnic peers	Loss of co-ethnic peers	Total
A. All individuals			
No loss of peers	2,504 (38.58%)	0	2,504 (38.58%)
Loss of peers	1,203 (18.54%)	2,783 (42.88%)	3,986 (61.42%)
Total	3,707 (57.12%)	2,783 (42.88%)	6,490 (100%)
B. Individuals in small teams (<= 27 team members)			
No loss of peers	2,259 (69.06%)	0	2,259 (69.06%)
Loss of peers	387 (11.83%)	625 (19.11%)	1,012 (30.94%)
Total	2,646 (80.89%)	625 (19.11%)	3,271 (100%)
C. Individuals in large teams (> 27 team members)			
No loss of peers	245 (7.61%)	0	245 (7.61%)
Loss of peers	816 (25.35%)	2,158 (67.04%)	2,974 (92.39%)
Total	1,061 (32.96%)	2,158 (67.04%)	3,219 (100%)

Notes: The table shows the number of individuals that experience the loss of a co-ethnic peer by team size.

Table A.18: BASELINE REGRESSION USING VARIOUS DEFINITIONS OF TEAM SIZE

A. Small teams defined using different percentiles

	Small teams (<=25th percentile, <=10 team members) (1)	Small teams (<=30th percentile, <=13 team members) (2)	Small teams (<=40th percentile, <=20 team members) (3)	Small teams (<=60th percentile, ¡= 36 team members) (4)	Small teams (<=70th percentile, <=51 team members) (5)	Small teams (<=75th percentile, <=63 team members) (6)
Loss of peer	0.013	0.013	0.016	0.014	0.014	0.014
	(0.005)***	(0.005)**	(0.005)***	(0.005)***	(0.005)***	(0.005)***
	[0.007]*	[0.007]*	[0.006]***	[0.005]***	[0.005]***	[0.004]***
Loss of co-ethnic peer	-0.071	-0.072	-0.090	-0.088	-0.081	-0.083
	(0.023)***	(0.024)***	(0.024)***	(0.025)***	(0.025)***	(0.024)***
	[0.032]**	[0.031]**	[0.029]***	[0.028]***	[0.026]***	[0.026]***
Observations	10,012	11,758	16,170	24,521	28,562	31,217

B. Large teams defined using different percentiles

	Large teams (>25th percentile, >10 team members) (1)	Large teams (>30th percentile, >13 team members) (2)	Large teams (>40th percentile, >20 team members) (3)	Large teams (>60th percentile, >36 team members) (4)	Large teams (>70th percentile, >51 team members) (5)	Large teams (>75th percentile, >63 team members) (6)
Loss of peer	0.011	0.009	0.004	0.007	0.012	0.021
	(0.007)	(0.007)	(0.008)	(0.012)	(0.012)	(0.020)
	[0.006]*	[0.006]	[0.007]	[0.009]	[0.012]	[0.017]
Loss of co-ethnic peer	-0.110	-0.076	0.009	-0.011	-0.484	-0.750
	(0.125)	(0.141)	(0.168)	(0.271)	(0.325)	(0.666)
	[0.111]	[0.121]	[0.138]	[0.244]	[0.358]	[0.641]
Observations	31,702	29,956	25,544	17,193	13,152	10,497

Notes: This table reports the coefficient estimates of the regression in equation 2 in the paper using the sample of employees whose H-1B visa extension was neither denied nor filed. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied. Columns 1 to 6 use different thresholds to define small and large teams. Standard errors clustered at the team level are reported in parentheses, while standard errors clustered at the individual level are reported in brackets: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.19: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS: REDUCED FORM AND PLACEBO TEST

Sample (Year)	Balanced (2014-2018)		Unbalanced (2008-2018)	
	All	No loss of peers	All	No loss of peers
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
FiledPeer	0.003**	0.002	0.004***	0.003*
	(0.001)	(0.001)	(0.001)	(0.002)
FiledPeer × Same ethnicity	-0.003**	-0.002	-0.003**	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Mean of outcome	3.610	3.610	3.435	3.435
Number of individuals	3,448	3,448	6,493	6,493
Number of units	430	430	836	836
Observations	17,240	14,409	41,714	38,695
R-squared	0.500	0.523	0.413	0.418

Notes: We report reduced-form estimates using the balanced panel data in columns 1-2 and the unbalanced panel data in columns 2-3. A placebo test using the sample of those who did not lose any peers is conducted in column 2 and column 4, respectively. *FiledPeer* is an instrument capturing the percentage of team members whose H-1B visa extension was filed on team size. Standard errors are clustered at the team level: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.