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

Prithwiraj Choudhury[*], Kirk Doran[†], Astrid Marinoni[‡], and Chungeun Yoon[§]

March, 2024

Abstract

We study how restrictive immigration policies that result in the unexpected loss of co-workers affect the performance of skilled migrants employed in organizations. Specifically, we examine the impact of the loss of team members on their co-workers' performance in response to the unexpectedly increased denials of extensions of H-1B work visas in the United States beginning in 2017. Losing a team member generally has a positive albeit economically insignificant effect on the performance of workers left behind. However, we find that individuals who lost peers of the same ethnic background experience a substantial decrease in their performance. To confirm that our results are not plagued by the presence of unobservable team or individual features that might impact visa-denial decisions, we build an instrumental variable that exploits the fixed duration of the H-1B visa. Heterogeneity analyses suggest that our result is driven by workers in small teams, teams working on atypical tasks, and ethnically homogeneous teams. These analyses hint at the fact that ethnic ties may boost individual performance through preferential channels of knowledge and information spillovers.

JEL classification: J24, J61, L25

[*]Harvard Business School
[†]University of Notre Dame and IZA
[‡]Georgia Institute of Technology
[§]KDI School of Public Policy and Management

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). 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]

Despite this, 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). One of the most prominent examples of this was former President Trump's adoption in 2017 of stricter immigration policies regarding temporary work visas, which substantially curbed the flow of high-skilled immigrants to the United States, including academics (Chinchilla-Rodrıguez et al., 2018). These changes were met with concern by many CEOs of major U.S. technology companies 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]

These regulations wield substantial influence over immigrant mobility because they are capable of reshaping the trajectory of immigration across different regions and nations. Their pivotal role stems from the profound implications they hold for both companies and immigrant workers alike. For instance, prior research has demonstrated that companies derive advantages from the exchange of knowledge between local and immigrant workers (Choudhury & Kim, 2019), as well as from the networks that immigrants can access within a specific location (Hernandez & Kulchina, 2020). Moreover, studies have shown that companies experiencing worker emigration from their home country can benefit from knowledge spillovers emanating from the workers' new destinations (Oettl & Agrawal, 2008b; Wang, 2015; Choudhury, 2017). For immigrant workers, the decision to relocate to a particular destination profoundly impacts their future career trajectory and also contributes to the

[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)

labor pool available for other firms (Choudhury et al., 2023). Tighter regulations could potentially disrupt and influence company-driven migration, leading to considerable economic repercussions for both businesses and immigrant workers.

In general, prior literature has found evidence of a negative connection between more restrictive immigration policies and broad economic outcomes at the regional level (e.g., Kerr & Lincoln, 2010; Clemens, 2011). However, it is unclear how stricter immigration policies influence individual worker performance within firms. Given this, we ask how the unexpected loss of employees due to the implementation of more restrictive immigration policies affects the performance of individual workers left behind within a firm. On the one hand, given the well-established tendencies of diminishing marginal product (Clark, 1888) and hiring on the margin (Brooks, 1974), the effect of losing a colleague on the individual performance or output of workers who remain at the firm could be very small, or even null. 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. 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 specifically ask whether there are any differential effects on worker performance, defined as employee ratings, in losing a co-ethnic versus a non-co-ethnic peer. Understanding these effects within firms will be important for managers who need to adjust workplace composition and policies on the fly amid ever-increasing immigration restrictions.

Answering this question is challenging because of the inherent endogeneity of departures and the scarcity of detailed individual-level data within firms. In this paper, we attempt to circumvent these problems 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 workers' 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

[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).

losing members.[4] We leverage the "Buy American, Hire American Act" as an exogenous policy event, which led to increased denial rates (i.e., increased probability of treatment) after its adoption in 2017, and we employ a difference-in-difference specification with staggered treatment, where workers within teams can be treated at different points in time and multiple times. By exploiting 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 co-worker on individual performance within teams. Most importantly, 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 probability 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 at a point in time 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.

Our results highlight how, on average, stricter immigration policies resulting in the loss of a co-worker tend to increase the individual performance of those left behind (Brooks, 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 employees tend to increase each other's performance. Specifically, we find that a 1% loss of same-ethnicity team members decreased an individual's performance rating by about 2% compared to their performance prior to losing a team member. In an average project team of eight members, the loss of a peer from the same ethnicity reduced the performance of the remaining team members by 20%. 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

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

theories that might explain our results.

We then try to explore which underlying mechanisms can explain our results. On the one hand, it might be that losing co-ethnic employees 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., 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 team and worker characteristics suggest that our results can be explained by the reduction in knowledge transfer and learning occurring among co-ethnic workers rather than by social incentives. In particular, we can shed light on this through two aspects: loss of workers by tasks and loss of workers 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 employees; and (ii) the loss of co-ethnic employees decreases the performance of junior workers, especially when a lost colleague was a co-ethnic senior employee. These two results highlight how co-ethnic individuals relying on irreplaceable knowledge and co-ethnic individuals dependent heavily on knowledge transfer processes are more exposed to the detrimental effects of peer loss. In addition, our results suggest that individuals belonging to small teams or ethnically homogeneous teams may be particularly affected by the loss of co-ethnic peers. Turning our attention to workers’ individual characteristics, the results are more mixed. However, our regressions hint at the fact that the performance of male workers with relatively low salaries and low hierarchical positions within the firm may decline the most after the loss of employees 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 worker 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. 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. (2015) 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., 2023). 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) found that Trump's executive order banning new work visas decreased the market valuation of public companies by roughly $100 billion. In the context of entrepreneurship, stricter immigration policies have negative effects on VC funding and IPO probability (Dimmock et al., 2022), as well as on immigrant entrepreneurship rates of funding (Acosta & Marinoni, 2023). 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. Other research explores how immigrants and firms can establish cross-national connections in the context of innovative outcomes (Fry & Furman, 2023; Kang, 2024).

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). 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).

Finally, 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 non-collaborators in the field. Waldinger (2012) finds no impact on peer performance when investigating the dismissal of high-quality scientists in Nazi Germany. 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 importantly, we aim to understand how ethnicity moderates the relationship between the loss of a peer and the performance of the remaining individuals.

2 Conceptual Framework

Stricter immigration policies leading to the departure of an employee could have significant consequences on the productivity of the remaining workforce. On one hand, the departure of a colleague might negatively affect the performance of the workers left behind, potentially resulting in the loss of a vital collaborator. On the other hand, it is conceivable that the performance of the remaining employees could see an uptick, particularly if they are compelled to compensate for the absence of their coworkers. Research exploring the impact of peers leaving or joining a variety of contexts as a consequence of policy implementations or major political events has yielded mixed findings. For example, following the collapse of the Soviet Union, the influx of immigrant Soviet mathematicians to the United States led to a decline in the performance of native American mathematicians in the same fields (Borjas & Doran, 2012). In the case of high-quality scientists being dismissed in Nazi Germany, Waldinger (2012) found no decrease in the performance of remaining colleagues.

This paper diverges from previous research by redirecting attention away from the interactions among inventors and researchers, and instead, centers on the dynamics among co-workers within teams and firms. In addition, we aim to shed light on a new aspect of the phenomenon related to worker departures, which has largely been overlooked by past literature: the loss of *co-ethnic* workers 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, employees who have to unexpectedly leave their teams might stop contributing both "know-what" and "know-how" knowledge to their co-workers. 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 (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. Other studies look at diaspora and brain-grain effects across countries in the context of co-ethnic scientists (Breschi et al., 2017). Still, other studies emphasize this phenomenon while investigating cross-national trade (Rauch & Trindade, 2002) and cross-country citation patterns following scientists' movements (Oettl & Agrawal, 2008a). 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 and worker 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., 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 ethnic ties might be particularly responsive to these dynamics. Given that co-ethnic ties are likely to motivate social incentives and social pressure (Bonacich, 1973; Portes & Sensenbrenner, 1993), losing a co-ethnic peer could result in a decline in individual performance.

We 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 and exploiting within-firm microdata. In particular, the enactment of the "Buy American, Hire American" Act in April 2017 changed the HB-1 extension requirements, among other provisions.

3 The H-1B 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.[5] 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

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

the lottery system has been in use since 2013 (Pathak et al., 2022).

In general, the application process for a new H-1B visa is costly and demanding. The petitioning employer has to meet strict requirements[6] and has to prove that the employee is qualified for a specialty occupation.[7]

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.[8]

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 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.

In general, the H-1B visa program provides an ideal context to study our research question, given that

[6] 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.

[7] 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.

[8] 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.

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. 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.

The company's employees tend to be assigned relatively high 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.[9] Information about workers' visa

[9]The company exclusively employs foreign nationals, and specifically Indian nationals in the Silicon Valley location. The employees in our sample represent roughly 92% of the workforce in this company. The remaining 8% hold L-1 visas or green cards.

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, we have information about applications, approvals, and denials of the H-1B visa extensions from 2014. Figure 1 shows the trend in denials of the H-1B visa extensions in our sample.[10] 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 satisfaction, ability to meet deadlines, and number of tasks completed, rather than on subjective supervisor evaluations. Employee ratings play an important role in the company, and they determine salaries, promotions, and terminations[11] Figure A.2 in the Appendix plots histograms of the average ratings in our data at the individual level and at the team-project level, while Figure 2 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.2 shows some summary statistics related to ethnicities while outlining our main categories; Table 1 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 country, historically a collection of diverse provinces with distinct cultural identities, saw the formation of states post-independence based on

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

[11]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.

linguistic and cultural similarities (Menon, 1955). This unique historical evolution, marked by a rich tapestry of languages, religions, and customs, positions Indian subethnicities on par with traditional ethnic groups often studied in immigration research. Consequently, our findings hold relevance and potential applicability to scenarios involving well-defined ethnic groups.

Table 2 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; 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 3 shows the distribution of team size at the team (Panel A) and individual levels (Panel B). 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). Panel B 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.

In Table 3, we report peer loss by team in Columns 1 and 2. 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. Table A.3 in the Appendix reports the distribution of the number of teams (by team size) that lost at least one member. When looking at the same statistic at the individual level (Columns 3 and 4 of 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.

[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).

Table A.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.[14] 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, and co-ethnicity is determined at the individual and not at the team level. Table A.5 in the Appendix shows a more detailed background of peer loss by team size.

4.2 Empirical Strategy

Our empirical strategy exploits variation in the decisions on H-1B visa extensions. We start our analysis by employing a difference-in-difference specification with staggered, heterogeneous treatments, 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 5.1.1, 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 take into account two key facts: firstly, that applications could either be approved or denied; and secondly, that while there were no H-1B visa denials in our sample during our pre-period years (i.e., 2014 and 2015), this number increased sharply after the enactment of the Executive Order, as shown in Figure 1 (Panel B). 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., "treated" team members who experienced loss of peers) with the subset of these who had no team members whose extensions were denied ("not-treated" team members who did not experience loss of peers). We exclude all teams that are composed of only one person from all our regressions. We measure the association between the loss of team members and performance in a staggered difference-in-difference framework with heterogeneous non-absorbing treatment where individuals (within teams) can experience peer loss in different years with heterogeneous treatments varying in intensity.[15]

Specifically, our study spans three years before and two years after the Executive Order (EO) implementation (2014-2018), with the change occurring in early 2017. As our treatments are staggered and can turn on and off, we

[14]The fact that most losses are co-ethnic losses is not especially surprising given that most of the employees in our firm come from very few states. These states, with the exception of Tamil Nadu, are also some of the most populous states in India.

[15]The adoption of the "Buy American, Hire American Act" in 2017 is not the treatment in our specification, it just leads to a higher probability of treatment (i.e., peer loss) in the years after 2017.

can consider eight treatment cases in our analysis, as shown in Figure 4. The vast majority of our sample (97.5%) falls into the first four cases (rows 1 to 4), covering those never treated and those treated right after the policy change in 2017. However, the remaining subset (see Figure 1, panel A), as shown in rows 5 to 8, experienced peer loss a year before the policy change, i.e., in 2016.[16] Despite the first two years in our analysis serving as common pre-period to all observations, some units have one or two additional years of pre-periods, depending on their treatment year. For instance, units treated in 2017 (e.g., rows 2 and 4) have an extended pre-period that includes year 3. Units treated in 2018 (e.g., row 3) have an even longer pre-period, spanning years 1 to 4. In our baseline model, for every unit that gets treated at some point in time, the control group is represented by never-treated units as well as units that have not received treatment in that year, yet. As recent econometric studies have extensively analyzed these types of difference-in-difference models (e.g., De Chaisemartin & d'Haultfoeuille, 2020; De Chaisemartin & d'Haultfoeuille, 2023; De Chaisemartin & d'Haultfoeuille, 2024), we also supplement our baseline model with the estimator recommended by De Chaisemartin and d'Haultfoeuille (2024) in Section 5.1.1.

To implement our baseline model, we employ the following specification:

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

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) in year t divided by the initial[17] number of employees on the team (or in the business unit) multiplied by 100.[18] This variable measures the loss of peers due to visa extension denials as a percentage. We chose a proportional treatment variable to capture the heterogeneous impact of peer loss within teams. Since team size can vary significantly, losing a member in a small team might have a much greater impact than losing the same member in a team consisting of several members.[19] We include the quartic of the age of person i in year t (i.e.,X_{it}) as this is a time-varying proxy for worker experience and thus ability, the individual fixed effect γ_i, and the year fixed effect τ_t. Team fixed effects (δ_j) are also included. We report the results from this estimation in Table 4, columns 1 and 3.

[16]Note that we do not have any observations that fit into the treatment pattern described in row 5, but we still include the row for completeness.

[17]That is, the initial team size before the occurrence of any visa extension denial. This considers only workers on H-1B visas, who comprise 92% of the workforce working in the United States for this company.

[18]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.

[19]In the paper, we present results from alternative specifications that employ a dummy variable as the treatment (Table 6).

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

$$Y_{it} = \beta PeerLoss_{it} + \alpha\,(PeerLoss_{it} \times SameEthnicity_{it}) + \theta X_{it} + \gamma_i + \delta_j + \tau_t + \epsilon_{it}, \qquad (2)$$

where $SameEthnicity_{it}$ is the number of co-ethnic peers whose visa extension denied in time t of worker i divided by the number of workers whose visa extension was denied in that team in time t. The interaction $PeerLoss_{it} \times SameEthnicity_{it}$ thus captures the number of co-ethnic workers lost by worker i over number of employees on the team multiplied by 100.[20] We report the results from this estimation in Table 4, columns 2 and 4.

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

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

where D_t is an indicator variable corresponding to a particular year t. The variable of $PeerLoss_i$ uses the total number of team members whose visa extensions were denied divided by the number of members in employee i's team multiplied by 100.[21] 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.

4.2.1 Instrumental Variable 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 of the magnitude of the $PeerLoss$. This means that, if anything, our OLS coefficients would provide 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

[20] For example, assume that there are four workers in a given team: A, B, C, and D. Assume also that A and B are co-ethnic; C and D are co-ethnic as well, but belong to a different ethnicity than A and B. Also, suppose that A and C have their visa extension denied and must leave the team. The value of $PeerLoss$ for all the workers in that team will be 2/4, because the team experiences the departure of two members and it is initially composed of four workers. The value of the variable $Same\,Ethnicity$ for workers B and D would be 1/2 as it is the ratio of the number of co-ethnic peers lost divided by the number of workers whose visa was denied in the team in that year. The $PeerLoss \times Same\,Ethnicity$ variable will then be 1/4 for both worker B and worker D.

[21] 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.

fact that workers experience the loss of a peer, there might still be some biases deriving from *time varying* 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. As a matter of fact, applicants are allowed to submit an extension to USCIS only during the six months leading up to the H-1B expiration date. Because the timing of the extension is fixed, based on the filing year of their first H-1B 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 when denials increased. Leveraging the fixed nature of visa duration, we build an instrument by considering the number of peers who filed an extension (in a given year) divided by team size. In our context, compliers are workers whose team members filed a visa extension which was denied as well as workers whose team members did not file a visa extension. Formally, we estimate the following first-stage and instrumented equations:

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

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 4 reports the results of our difference-in-difference 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,[22] and a balanced sample that considers the 2014–2018 period.[23] The models using the balanced sample are our preferred specifications.[24]

[22]Despite the data on ratings going back to 2008, we have data about visa extensions only from 2014 onward. In our sample, we start observing the first denials from 2017 (included) onward.

[23]The unbalanced sample encompasses four groups of employees: workers who had their extension denied, workers who had their extension approved, workers who experienced the loss of a colleague, and workers who did not. The balanced sample, which includes only employees for whom we have performance ratings for every year, comprises only three categories of employees: employees who did not have their visa denied, employees who experienced peer loss, and employees who do not experience peer loss.

[24]The coefficients in the balanced model consistently represent the average effect over all cross-sectional units at any point in time.

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 the 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 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 4 shows a negative and significant coefficient for the interaction term ($PeerLoss \times Same\,Ethnicity$). Our results suggest that a 1% loss of team members due to visa denials decreased ratings by 0.058 (1.6%) within teams.[25] 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%. It is worth noticing that the total effect of $PeerLoss + (PeerLoss \times Same\,Ethnicity)$ is different from zero at the 10% percent level: given an average team with eight members, the total effect suggests that losing a same-ethnicity peer decreased the performance of those left behind by 16%. Figure A.3 in the Appendix 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 ($PeerLoss \times Same\,Ethnicity$) 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 same-ethnicity peers when the visa extension denials surged in 2017 and 2018. Panel B of Figure 5

[25] 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.

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.

5.1.1 Validity of the Identification

We investigate the validity of our main empirical model by regressing variables that should not be affected by visa extension denials. H-1B visa extensions, in our sample, began to be filed and approved in 2014. To start, we examine the period before any denials happen in our sample, i.e., 2008–2014. Table A.1 in the Appendix 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. Table A.6 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. Figure 6 shows more detailed differences between our treated and untreated groups by rating, gender, and age.

The key identifying assumption of our difference-in-difference strategy is that the outcomes of employees who experienced peer loss and the outcomes of the employees who did not lose any team member must not vary in the absence of extension denials. Figure A.4 shows pre-trends of ratings among employees by their statuses up until 2013. We can also 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 presents coefficient estimates based on Equation 3 relative to the base year (2013): overall, no coefficients are significant for the pre-period. 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 Panel B.

It is worth noticing that our pre- and post-treatment periods are not clearly defined as in a traditionally non-staggered difference-in-difference model. In our setup, treatment is staggered as it can occur at different points in time: each individual can then have a different pre- and post- period. There is a common pre-period where no individual in our sample gets treated, which is in the years 2014 and 2015, as depicted in Figure 4. In general, Figure 5 (panel B) reassures us of the lack of significant pre-trends when considering those years. However, given our peculiar type of difference-in-difference, which features staggered, heterogeneous treatments that switch on and off, we also show pre-trends calculated by leveraging two recently developed difference-in-difference methods. Specifically, we re-run our primary analyses using the new methodologies introduced by Callaway and Sant'Anna (2021) and De Chaisemartin and d'Haultfoeuille (2024).

The first method entails modeling the staggered difference-in-difference with a classic dummy treatment variable, and the treatment remains activated once triggered, which represents a variation compared to our setup. Despite the mismatches with our initial specification, this model serves as a good robustness check for our findings as it can highlight how peer loss does not need to be repeated over time to have significant negative effects on performance.

The estimator proposed by De Chaisemartin and d'Haultfoeuille (2024) is more suitable for our empirical framework since it accommodates staggered heterogeneous treatment effects that switch on and off over time. Adding their model to our paper is very valuable as the estimator effectively addresses the biases commonly associated with more traditional models, which may lead to skewed estimates. Crucially for our analysis, it accounts for the bias from heterogeneous treatment effects, ensuring that variations in treatment intensity or type are accurately captured. This is particularly relevant since OLS-based traditional models presuppose a constant treatment effect across time and entities, potentially masking significant variations. When treatment effects vary, estimators might not accurately reflect the actual impact of the treatment on specific groups or time periods, possibly leading to incorrect conclusions about the treatment's effectiveness. In our case, this implies treating the loss of each peer as constant across units, which might not be an unreasonable assumption, although it is also possible that the marginal effect of peer loss may decrease with the number of losses.

Panels A of Figure A.5 and Figure A.6 present event-study plots using the Callaway and Sant'Anna (2021) methodology, while Panels B of Figure A.5 and Figure A.6 display the same plots using the methods proposed by De Chaisemartin and d'Haultfoeuille (2024). None of the graphs exhibit pretrend effects, and all of the graphs reveal a negative and statistically significant coefficient for co-ethnic peer loss after year 0 (the year in which co-ethnic peer loss occurs). Overall, these tests provide evidence of the validity of our empirical strategy and the absence of major biases in our findings. For all three methods employed (standard fixed-effects, Callaway and

Sant'Anna (2021), and De Chaisemartin and d'Haultfoeuille (2024)) we show robustness checks as suggested by the work of Roth (2022) and Rambachan and Roth (2023) in the Appendix (Figures A.7 and A.8).

5.1.2 Instrumented Results

Despite the apparent similarities between workers who have experienced peer loss and those who have not, as highlighted in the analyses above, we further ensure that visa denials are independent of the time-varying characteristics of workers and teams. This is achieved by using the instrumental variable outlined in Section 4.2.1, namely, the proportion of visa extensions relative to team size. In general, this instrument is highly correlated with our endogenous variable: the coefficient of the first stage is 0.067 with a standard error of 0.011, which translates to a P-value lower than 0.01.

Our instrument is valid only if the exclusion restriction is satisfied, i.e., the number of filed extensions ($Filed$) must affect performance only through the number of rejected applications. Moreover, the timing of the application should not be correlated with performance. While the latter condition is satisfied by the strict USCIS rules that regulate the timing of extension filing, there is less clarity regarding the fulfillment of the former condition. We can verify the validity of the exclusion restriction by conducting a placebo test that checks whether the performance of workers who did **not** lose any team members is impacted by the mere filing of an extension by a member of the team. This reduced-form estimate should provide evidence of the exclusion restriction by showing insignificant effects of filing an extension (i.e., our instrument) on our outcome variable if there is no loss of peers. Filing an extension should affect our outcome only through losing a peer. Table A.7 in the Appendix shows the results of this exercise while using the sample of individuals who did not lose any peers (columns 2 and 4). Columns 1 and 3 use our baseline sample. As expected, the coefficients in columns 1 and 3 are significant, highlighting the relevance of our instrument, while the ones in columns 2 and 4 are not, thus reassuring us of the validity of the exclusion restriction.

Table 5 presents the results of our instrumented specifications. Analyzing both balanced and unbalanced samples, we find consistent evidence supporting our hypothesis: the loss of co-ethnic members negatively impacts the performance of remaining peers. Specifically, Columns 1 and 2 display a generally greater coefficient for $PeerLoss$ than the one found in Table 4. The main effect is also less precise, with a P-value slightly greater than 0.1. This pattern suggests that our initial estimates for the coefficient $PeerLoss$ might have been slightly underestimated. One explanation for this underestimation is a potential bias arising from less-skilled or less-experienced workers being more prone to visa extension denials.

The coefficient for the interaction term ($PeerLoss \times Same, Ethnicity$) in our preferred specification (Column 2) aligns closely with that in our OLS specifications (Column 2 of Table 4), suggesting robustness in this aspect. However, when considering the sum of the main effect and the interaction effect (in Columns 2 and 3), we find it not significantly different from zero. This result suggests that while individual components of the model are significant, their combined impact does not lead to a statistically significant deviation from the baseline when considered together. However, this difference primarily stems from a larger coefficient for the main effect, rather than a reduction in the magnitude of the interaction.

While in our main model we use a proportional treatment, 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 6 shows our main specification using a dummy-based variable capturing whether the individual has experienced the loss of at least one member. Column 1 shows the effect of the loss of at least one member on peers' performance. Column 2 introduces the interaction (*PeerLoss* x *Same Ethnicity*). In general, results are robust, despite the borderline insignificance of the interaction term. We argue that the loss of significance is coherent with our theoretical and empirical setup: given the wide range of team size in the company, the effect of losing one peer gets diluted as team size grows.

From a theoretical point of view, the loss of a co-worker might have heterogeneous effects in teams of different sizes: when considering knowledge, it might be harder for workers in small teams to replace knowledge flows and learning dynamics once a member of the team is forced to leave. When considering our social mechanisms, one could argue that social dynamics such as kinship might be more salient and easier to emerge in small teams. We also present a similar version of this specification by using a dummy variable as well as a count of workers lost as a treatment variable while controlling for team size. Table A.9 in the Appendix shows that our main results are confirmed.

As an additional analysis, 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.8 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 a significant and negative effect 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 in 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.

5.1.3 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.10 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.11 in the Appendix show the insignificant coefficients on the interaction term ($PeerLoss \times OtherEthnic$) according to modified Equation 2. $OtherEthnic$ is a dummy that captures whether worker i and the departing worker do not share the same birth state.[26] The loss of non-co-ethnic peers due to 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 chose 283 other employees as a placebo treatment group, without replacement, and constructed a new right-hand side variable.

[26] Here, we use a more granular way to define co-ethnicity to define $OtherEthnic$ as the simple inverse of $Same\,Ethnicity$.

We then reestimate the regression in Equation 3 and report the coefficient on ($PeerLoss \times Same\,Ethnicity$) of the placebo treatment variable. We repeat this test 10,000 times with random shuffles. Figure A.9 in the Appendix 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.

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.12 in the Appendix shows how our results are robust to the omission of these groups.

5.1.4 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.2 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.13): employees' performance decreased when they faced the loss of co-ethnic peers who could speak their own language.

It may be a concern that the majority of our employees come from a few specific regions, leading to two macro areas, North and South, mainly driving findings. However, we can leverage the information we have about each employee's state of birth to create a more detailed ethnic classification. This approach, though extremely valuable, leads to some limitations in statistical power, as the occurrence of peer loss becomes less frequent with more precise classification. Despite this challenge, Table A.14 presents the results of our standard specifications using states to define co-ethnicity. While the direction of our coefficients remains consistent across both models, only the interaction observed in the unbalanced specification is statistically significant.

An alternative way to classify ethnicity is to exploit an initiative of the government of India, that, in order to preserve and promote the country's diverse cultures, decided to set up Zonal Cultural Centres (ZCCs), whose aim is to organize various cultural activities and programs on a regular basis in their member states throughout the year[27]. While these zones are mostly governmental in nature, they are a good proxy for the country's different cultures. The government identified seven zones, which comprise on average seven states each, with overlapping areas (i.e., states can belong to different zones depending on their cultural traits). Table A.15 in the Appendix lists details about the zones and the member states. Table A.16 shows that our results are robust when employing this definition.

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.17 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.17 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.[28] 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 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.[29] Table A.18 shows that the results are robust to

[27] More information is available at https://pib.gov.in/PressReleaseIframePage.aspx?PRID=1882847

[28] 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).

[29] 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.

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.19 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 the 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.20 shows how denial rates are, in general, stable across subethnicities, 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.21 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 results. 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.22 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 4). Overall, this reassures us that the co-ethnicity coefficient (*Same Ethnicity*) does not capture 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 (Jäger & Heining, 2022). 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.[30] Specifically, we use Jaccard's similarity index on team-name similarity, and we examine the effect of the loss of a co-ethnic peer separately for

[30] 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.

teams with low and high task uniqueness (using the median as the reference). The rationale of this measure relies on the fact that team names in the company we study are a direct reflection of the technology and functional domain on which the project is based. Thus, 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 related to a standard technological domain for the firm, which we classify as "typical" for the company. Other teams perform unique tasks that are related to rare or unconventional technological domains. For instance, the "GRC-IGRC Consult" team is responsible for providing consulting services related to governance, risk management, and compliance. This is an example of a team name scoring very high in uniqueness. We classify the tasks these teams are responsible for as "atypical." Workers in these teams possess especially complex skill sets and a unique knowledge profile, as confirmed by their higher wages compared to those in other teams. If one of these peculiar teams were to lose a member, the organization might not readily replace her knowledge and skills.

Table 7 shows that the negative effect of the loss of co-ethnic peers is only present if we consider teams with atypical tasks, suggesting it is the loss of knowledge and skills, rather than social incentives, that drives the decline in performance of co-ethnic members. The interaction coefficients are significantly different from one another in both models.

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 senior employees, 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 senior colleagues' knowledge and skill. We first categorize each employee as junior or senior based on position level.[31] Then we analyze the impact of a loss by classifying departing and remaining team members by position.

[31] 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

Table 8 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 senior employees. This might point to the fact that knowledge transfer and learning among team members seem to play more prominent roles than social incentives in explaining our results. Though 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 senior employees more. It is worth noticing that despite the coefficient for senior peer loss is higher than the coefficient capturing junior peer loss, these coefficients are not statistically different from each other. 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 senior workers already possess sufficient knowledge and skills and are not particularly affected by the loss of other knowledgeable senior or junior employees. Overall, our evidence points to the fact that impaired and weakened knowledge flows, rather than social incentives, drive the decrease in performance of co-ethnic members.

It might be possible that the effect we find is related to a kinship-related dynamic for which senior employees decide to sponsor and champion junior peers of the same ethnicity. If this mechanism were at play, we should observe a drop in junior employees' performance independently of which tasks the team has been assigned. Table A.23 in the Appendix shows how only junior employees who experienced the loss of a senior employee in teams assigned to atypical tasks experience a reduction in their performance. This table effectively underscores the critical role of knowledge exchange within teams, as it shows how individuals with less expertise in environments where knowledge is paramount suffer the greatest impact from the loss of co-ethnic peers.

Having clarified which mechanism is most likely 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.24 in the Appendix). Table A.25 in the Appendix shows that the negative effects of the loss of co-ethnic peers are

presidents, and senior vice presidents.

generally driven by workers in small teams.[32] This is also confirmed by Figure A.10 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.26 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. Columns 3 and 4 in Table 6 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 A.27 in the Appendix shows that workers belonging to less ethnically diverse teams experienced stronger negative shocks than workers in more ethnically diverse teams. This result is 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 A.28 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 A.29) and workers with low salaries (Table A.30). 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 A.31 in the Appendix 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.[33] This result is consistent with a large literature examining the effect

[32] 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. It is also worth noticing that the two interaction coefficients in Table A.25 are not statistically different from one another.

[33] 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).

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.[34]

6 Discussion and Conclusion

This paper examines the impact of skilled migrants' performance following the sudden loss of peers due to stringent immigration policies. Utilizing detailed microdata from a major firm, including workers' visa statuses, and focusing on the unintended exit of team members caused by visa rejections, we find that those who lost co-ethnic peers saw notable declines in performance. Our study delves into the underlying mechanisms by analyzing extensive team and individual characteristics, identifying those most affected by the loss of co-ethnic colleagues. We find that small teams, teams working on atypical tasks, and ethnically homogeneous teams are more sensitive to the loss of peers. In general, 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.

This paper enriches several strands of academic literature. It contributes to studies on the economic impacts of stringent immigration policies as investigated by Kerr and Lincoln (2010) and Doran et al. (2022). Diverging from previous work that focused on firm-level outcomes, this study delves into the effects of immigration policies on internal firm dynamics and individual worker performance. This paper also adds to the discourse on the effects of peer loss in professional settings, expanding on the works of Borjas and Doran (2012), Waldinger (2012), and Azoulay et al. (2019), by exploring how ethnicity moderates these impacts within firms. In the realm of co-ethnic ties, it also builds upon the findings of Hernandez (2014) and Kulchina and Hernandez (2016). In general, our research uncovers a previously unexplored mechanism: the way in which co-ethnic similarities among immigrants forge preferential channels for knowledge exchange. These channels are so influential that they amplify the impact of immigration policy changes, leading to disproportionate effects on individual 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 all our workers are foreign-born. It is unclear whether the mechanisms at play in our context also apply broadly to native employees. Third, the lack of data and the COVID-19 pandemic prevent us from studying the long-

[34] Tables A.32, A.35, A.33, A.34, A.36, A.37, A.38 in the Appendix show all the above heterogeneous analysis while exploiting a specification with a triple interaction.

term effects of peer loss. Fourth, most of our workers come from two regions, which might pose a problem for internal and external validity. Finally, we capture ethnicities within a single country, but we do not consider heterogeneity at the state level. 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 in within-firm dynamics and workers' performance. Further research could also be dedicated to examining what happens to the performance 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.[35] 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.[36]

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. We argue that managers should proactively ensure that co-ethnics who lose a peer have alternative mechanisms for accessing knowledge and getting mentored appropriately. Because both tacit knowledge residing in employees and intangible organizational routines are fundamental for firms (Nelson & Winter, 1982; Kogut & Zander, 1992), the decrease in performance of these knowledge-reliant teams might have a serious impact on the survival and growth of these companies.

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

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

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 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.[37] 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 and how firms should shape policies around this.

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

References

Acosta, C., & Marinoni, A. (2023). Uncertainty and immigrant entrepreneurship: Evidence from Brexit. *Organization Science (forthcoming).*

Azoulay, P., Fons-Rosen, C., & Graff Zivin, J. S. (2019). Does science advance one funeral at a time? *American Economic Review*, *109*(8), 2889–2920.

Azoulay, P., Graff Zivin, J. S., & Wang, J. (2010). Superstar extinction. *The Quarterly Journal of Economics*, *125*(2), 549–589.

Bahar, D., Choudhury, P., & Glennon, B. (2020). *An executive order worth $100 billion: The impact of an immigration ban's announcement on fortune 500 firms' valuation* (tech. rep.). NBER.

Bandiera, O., Barankay, I., & Rasul, I. (2009). Social Connections and Incentives in the Workplace: Evidence From Personnel Data. *Econometrica*, *77*(4), 1047–1094.

Bandiera, O., Barankay, I., & Rasul, I. (2010). Social Incentives in the Workplace. *Review of Economic Studies*, *77*(2), 417–458.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives*, *28*(2), 153–76.

Bonacich, E. (1973). A theory of middleman minorities. *American sociological review*, 583–594.

Borjas, G. J., & Doran, K. B. (2012). The Collapse of the Soviet Union and the Productivity of American Mathematicians. *Quarterly Journal of Economics*, *127*(3), 1143–1203.

Borjas, G. J., Doran, K. B., & Shen, Y. (2018). Ethnic Complementarities after the Opening of China. *Journal of Human Resources*, *53*(1), 1–31.

Breschi, S., Lissoni, F., & Miguelez, E. (2017). Foreign-origin inventors in the usa: Testing for diaspora and brain gain effects. *Journal of Economic Geography*, *17*(5), 1009–1038.

Brooks, F. P. (1974). *The mythical man-month: Essays on software engineering.* Datamation.

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of econometrics*, *225*(2), 200–230.

Chinchilla-Rodrıguez, Z., Bu, Y., Robinson-Garcıa, N., Costas, R., & Sugimoto, C. R. (2018). Travel bans and scientific mobility: Utility of asymmetry and affinity indexes to inform science policy. *Scientometrics*, *116*(1), 569–590.

Choudhury, P. (2017). Innovation outcomes in a distributed organization: Intrafirm mobility and access to resources. *Organization Science*, *28*(2), 339–354.

Choudhury, P., Khanna, T., & Sevcenko, V. (2023). Firm-induced migration paths and strategic human-capital outcomes. *Management Science*, *69*(1), 419–445.

Choudhury, P., & Kim, D. Y. (2019). The Ethnic Migrant Inventor Effect: Codification and Recombination of Knowledge across Borders. *Strategic Management Journal*, *40*(2), 203–229.

Clark, J. B. (1888). *Capital and its earnings* (Vol. 3). American economic association.

Clemens, M. A. (2011). Economics and emigration: Trillion-dollar bills on the sidewalk? *Journal of Economic perspectives*, *25*(3), 83–106.

De Chaisemartin, C., & d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, *110*(9), 2964–2996.

De Chaisemartin, C., & d'Haultfoeuille, X. (2023). Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey. *The Econometrics Journal*, *26*(3), C1–C30.

De Chaisemartin, C., & d'Haultfoeuille, X. (2024). Difference-in-differences estimators of intertemporal treatment effects. *Review of Economics and Statistics*, 1–45.

Dimmock, S. G., Huang, J., & Weisbenner, S. J. (2022). Give me your tired, your poor, your high-skilled labor: H-1b lottery outcomes and entrepreneurial success. *Management Science*, *68*(9), 6950–6970.

Doran, K., Gelber, A., & Isen, A. (2022). The Effects of High-Skilled Immigration Policy on Firms: Evidence from Visa Lotteries. *Journal of Political Economy*, *130*(10), 2501–2533.

Drucker, P. F. (1999). Knowledge-worker productivity: The biggest challenge. *California management review*, *41*(2), 79–94.

Fehr, E., & Goette, L. (2007). Do Workers Work More if Wages Are High? Evidence from a Randomized Field Experiment. *American Economic Review*, *97*(1), 298–317.

Foley, C. F., & Kerr, W. R. (2013). Ethnic Innovation and U.S. Multinational Firm Activity. *Management Science*, *59*(7), 1529–1544.

Freeman, R. B., & Huang, W. (2014). Strength in Diversity. *Science*, *513*(7518), 305.

Fry, C., & Furman, J. L. (2023). Migration and global network formation: Evidence from female scientists in developing countries. *Organization Science (forthcoming).*

Hernandez, E. (2014). Finding a Home away from Home: Effects of Immigrants on Firms' Foreign Location Choice and Performance. *Administrative Science Quarterly*, *59*(1), 73–108.

Hernandez, E., & Kulchina, E. (2020). Immigrants and foreign firm performance. *Organization Science*, *31*(4), 797–820.

Hjort, J. (2014). Ethnic Divisions and Production in Firms. *Quarterly Journal of Economics*, *129*(4), 1899–1946.

Ichino, A., & Falk, A. (2005). Clean evidence on peer effects. *Journal of Labor Economics*, *24*.

Jäger, S., & Heining, J. (2022). *How substitutable are workers? evidence from worker deaths* (tech. rep.). National Bureau of Economic Research.

Kang, J., H. Eklund. (2024). Fast friends: Understanding the impact of short-term visits on firms' innovation outcomes. *Organization Science (forthcoming).*

Kerr, S. P., Kerr, W., Özden, Ç., & Parsons, C. (2017). High-skilled migration and agglomeration. *Annual Review of Economics*, *9*, 201–234.

Kerr, S. P., Kerr, W. R., & Lincoln, W. F. (2015). Skilled Immigration and the Employment Structures of US Firms. *Journal of Labor Economics*, *33*(S1), S147–S186.

Kerr, W. R. (2008). Ethnic Scientific Communities and International Technology Diffusion. *Review of Economics and Statistics*, *90*(3), 518–537.

Kerr, W. R., & Lincoln, W. F. (2010). The Supply Side of Innovation: H-1B Visa Reforms and U.S. Ethnic Invention. *Journal of Labor Economics*, *28*(3), 473–508.

Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization science*, *3*(3), 383–397.

Koka, B. R., & Prescott, J. E. (2002). Strategic alliances as social capital: A multidimensional view. *Strategic management journal*, *23*(9), 795–816.

Kulchina, E., & Hernandez, E. (2016). Immigrants and firm performance: Effects on foreign subsidiaries versus foreign entrepreneurs. *Academy of Management Proceedings*.

Lang, K. (1986). A Language Theory of Discrimination. *Quarterly Journal of Economics*, *101*(2), 363–382.

Marx, B., Pons, V., & Suri, T. (2021). Diversity and Team Performance in a Kenyan Organization. *Journal of Public Economics*, *197*(104332).

Mas, A., & Moretti, E. (2009). Peers at Work. *American Economic Review*, *99*(1), 112–145.

Mayda, A. M., Ortega, F., Peri, G., Shih, K., & Sparber, C. (2023). Coping with h-1b shortages: Firm performance and mitigation strategies. *ILR Review*, *76*(5), 919–943.

Mayo, E. (1933). *The human problems of an industrial civilization*. New York, Macmillan.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual review of sociology*, *27*(1), 415–444.

Menon, V. P. (1955). *The story of the integration of the Indian states*. Longmans, Green; Co.

Miller, D. L., Shenhav, N., & Grosz, M. Z. (2019). *Selection into identification in fixed effects models, with application to head start* (tech. rep.). National Bureau of Economic Research.

Nelson, R. R., & Winter, S. G. (1982). *An evolutionary theory of economic change* (tech. rep.).

Oettl, A., & Agrawal, A. (2008a). International Labor Mobility and Knowledge Flow Externalities. *Journal of International Business Studies*, *39*(8), 1242–1260.

Oettl, A., & Agrawal, A. (2008b). International labor mobility and knowledge flow externalities. *Journal of international business studies*, *39*, 1242–1260.

Pathak, P. A., Rees-Jones, A., & Sönmez, T. (2022). Immigration lottery design: Engineered and coincidental consequences of h-1b reforms. *Review of Economics and Statistics*, 1–43.

Peri, G., Shih, K., & Sparber, C. (2015). STEM Workers, H-1B Visas, and Productivity in US Cities. *Journal of Labor Economics*, *33*(3), S225–S255.

Polanyi, M. (1961). *The tacit dimension*. University of Chicago Press.

Portes, A., & Sensenbrenner, J. (1993). Embeddedness and immigration: Notes on the social determinants of economic action. *American journal of sociology*, *98*(6), 1320–1350.

Rambachan, A., & Roth, J. (2023). A more credible approach to parallel trends. *Review of Economic Studies*, *90*(5), 2555–2591.

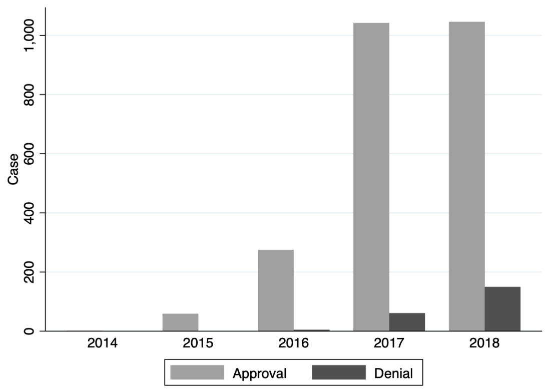
Rauch, J. E., & Trindade, V. (2002). Ethnic chinese networks in international trade. *Review of Economics and Statistics*, *84*(1), 116–130.

Rissing, B. A., & Castilla, E. J. (2014). House of green cards: Statistical or preference-based inequality in the employment of foreign nationals. *American Sociological Review*, *79*(6), 1226–1255.

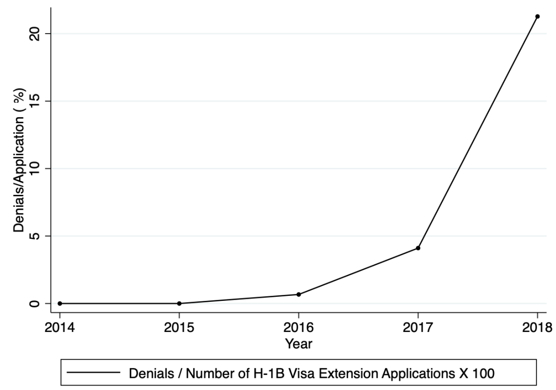
Rissing, B. A., & Castilla, E. J. (2016). Testing attestations: Us unemployment and immigrant work authorizations. *Ilr Review*, *69*(5), 1081–1113.
Roth, J. (2022). Pretest with caution: Event-study estimates after testing for parallel trends. *American Economic Review: Insights*, *4*(3), 305–322.
Waldinger, F. (2012). Peer effects in science: Evidence from the dismissal of scientists in nazi germany. *The Review of Economic Studies*, *79*(2), 838–861.
Wang, D. (2015). Activating cross-border brokerage: Interorganizational knowledge transfer through skilled return migration. *Administrative Science Quarterly*, *60*(1), 133–176.

Figures and Tables

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



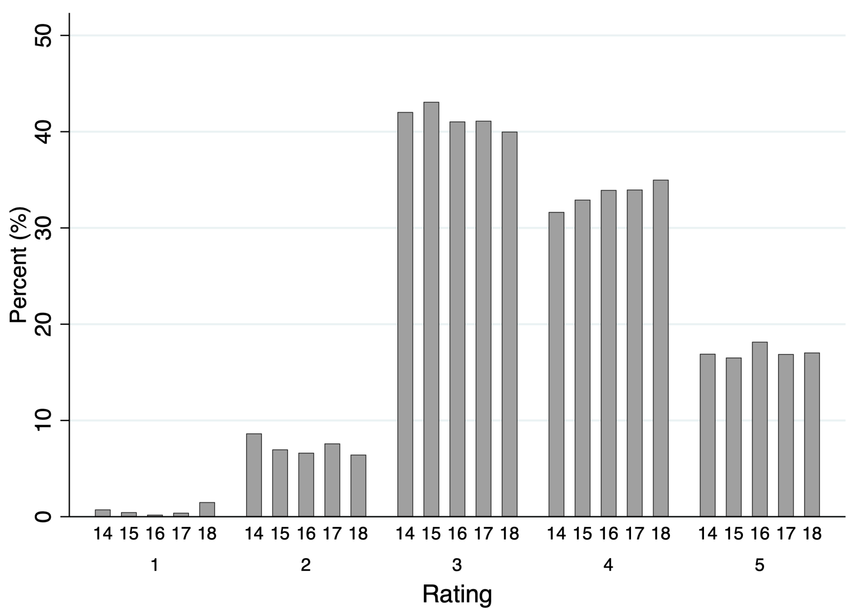
(a) Visa Approvals and Denials



(b) Denial Rate

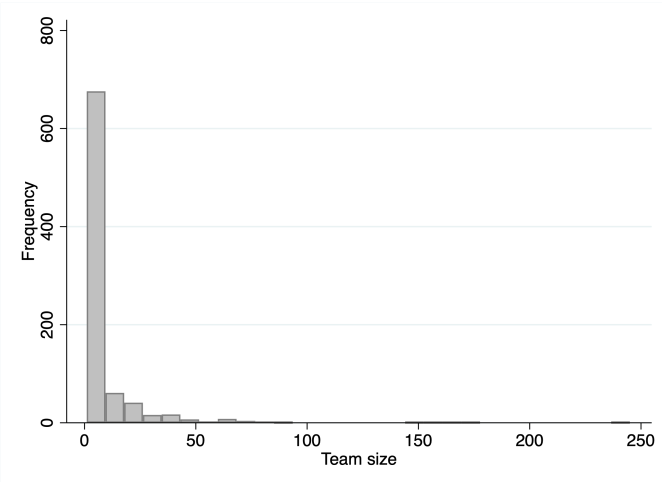
Notes: These figures plot the results of H-1B visa extensions by calendar year in our sample. Plot (a) presents the raw number of H1-B visa extensions approved and denied. Plot (b) shows the percentage of denied cases among the total number of visa-extension applications (%).

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

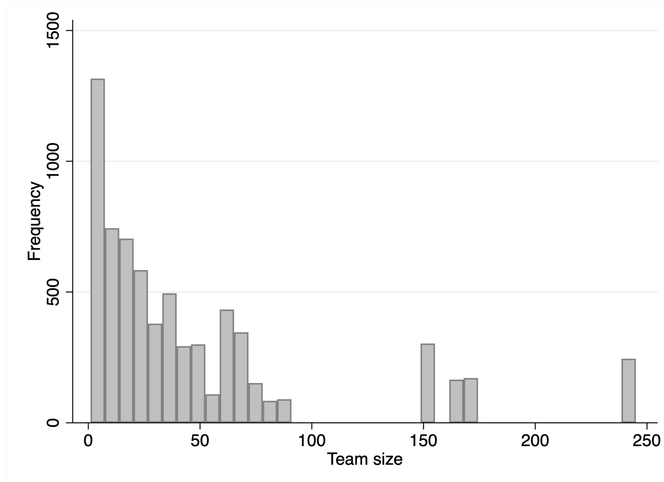


Notes: This histogram presents the percentage of average employee ratings, by whole number by year.

Figure 3: HISTOGRAM OF TEAM SIZE



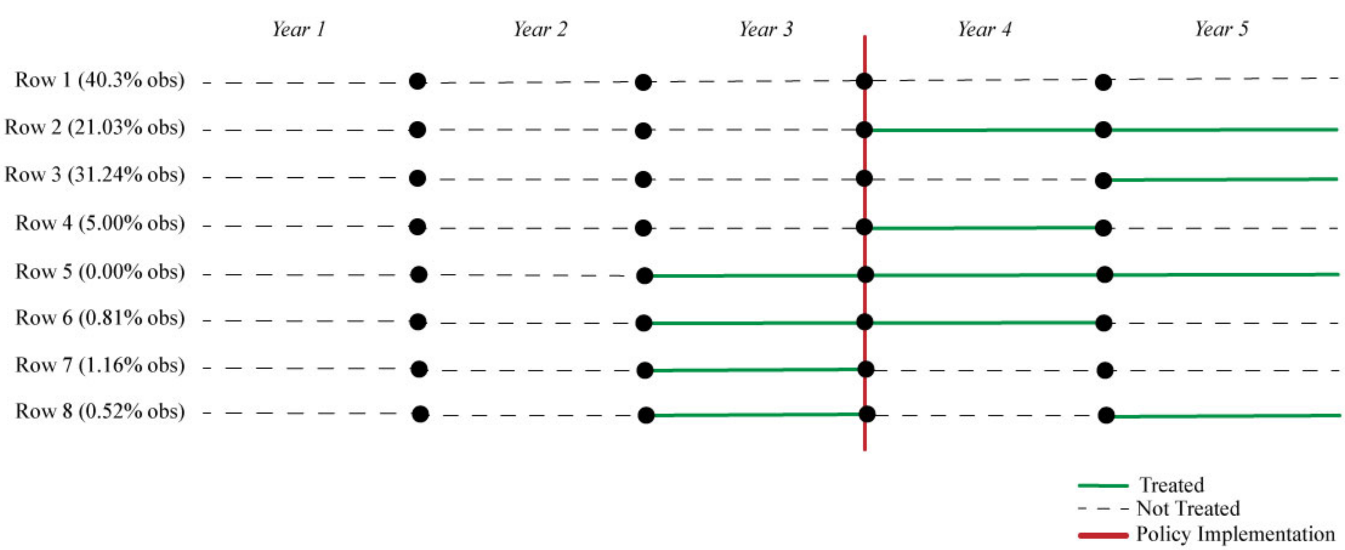
(a) Team level



(b) Individual level

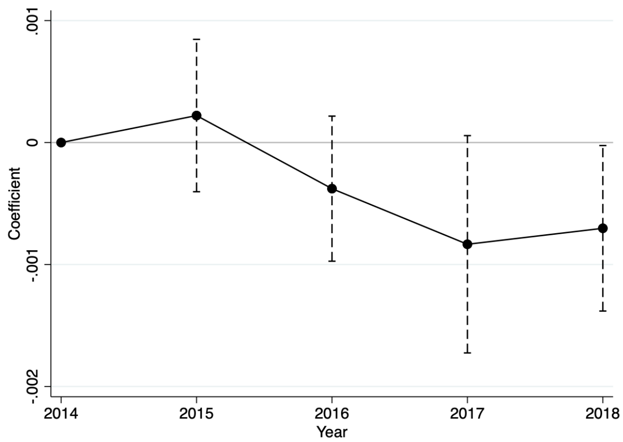
Notes: The histograms present the frequency of team size at the team level in plot (a) and at the individual level in plot (b), respectively.

Figure 4: STAGGERED DIFFERENCE-IN-DIFFERENCE WITH HETEROGENEOUS EFFECTS



Notes: the figure shows the eight treatment cases that could be present in our setup (each case is represented in a different row). Next to each row number, we report the percentage of observation in our balanced model that corresponds to each case.

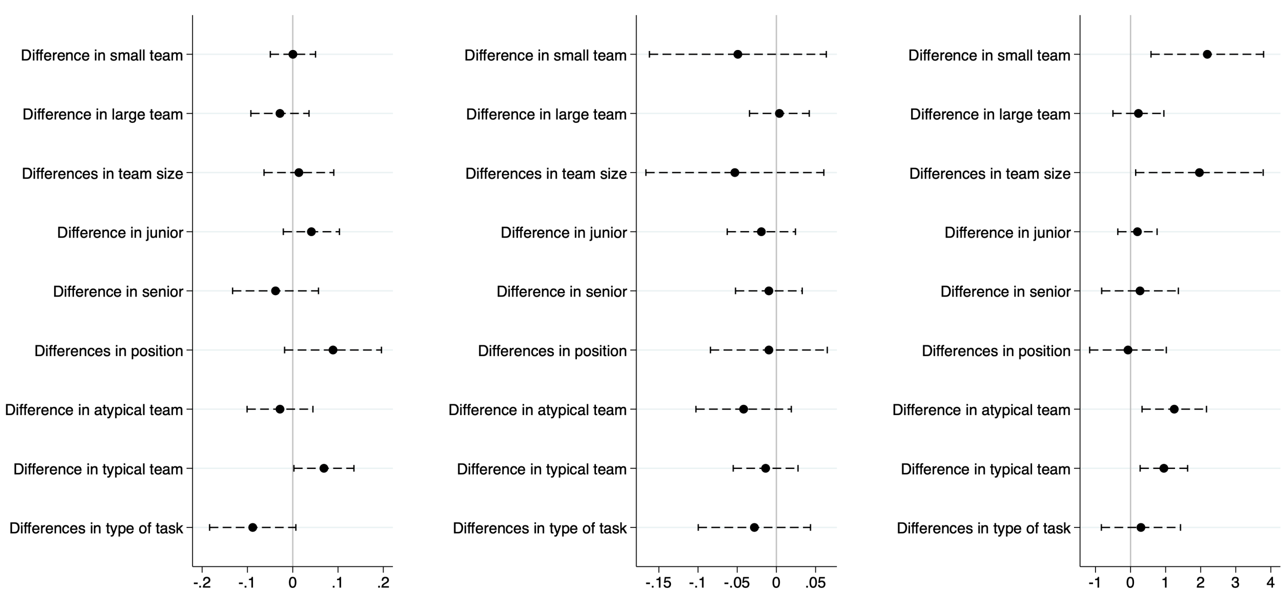
Figure 5: DIFFERENCE-IN-DIFFERENCES IN INDIVIDUAL RATINGS IN RESPONSE TO THE LOSS OF THE CO-ETHNIC PEERS



(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: BASELINE INDIVIDUAL CHARACTERISTICS BY TYPE



(a) Ratings (b) Gender (c) Birth year

Notes: The figures show the difference in baseline characteristics between those who lost their peers (treatment group) and those who did not lose their peers (control group) prior to any H-1B visa extensions filed in our sample across different subsamples. The differences in subsamples (3^{rd}, 6^{th} and 9^{th} row) show the variations between one group and another.

Table 1: 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 2: 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 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 3: NUMBER OF TEAMS AND INDIVIDUALS THAT EXPERIENCE THE LOSS OF A MEMBER

	Team Level		Individual Level	
	(1)	(2)	(3)	(4)
Loss of Peers	Frequency	Percent	Frequency	Percent
A. By loss of peers				
No	705	83.83	2504	38.58
Yes	136	16.17	3986	61.42
B. By number of lost peers				
0	705	83.83	2505	38.58
1	75	8.92	1284	19.78
2	33	3.92	929	14.31
3	11	1.31	492	7.58
4	6	0.71	260	4.00
5	4	0.48	185	2.85
6	2	0.24	106	1.63
9	2	0.24	200	3.08
11	2	0.24	378	5.82
13	1	0.12	154	2.37

Notes: The table shows the number of teams and individuals that experienced 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: 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 × Same ethnicity	-	-0.058*	-	-0.072***
		(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 the 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. All columns include worker, team, and year fixed effects. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 5: 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) × Same ethnicity	-	-0.048*	-	-0.046*
		(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 KP F-stat	32.810	23.810	37.580	25.504
Stock-Yogo 10% Max IV Size	16.38	19.93	16.38	19.93

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 the 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. All columns include worker, team, and year fixed effects. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 6: 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)
PeerLoss × Same ethnicity		-0.054	-0.121**	-0.039
		(0.034)	(0.062)	(0.038)
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 the 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 show the results from the same specification in Column 2, while splitting the sample depending on team size. All columns include worker, team, and year fixed effects. Standard errors clustered at the team level are reported in brackets: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 7: 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 × Same ethnicity	-	-0.306**	-	-0.034
		(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 (built 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 the 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. The mean of PeerLoss for atypical and typical tasks is 0.634 and 0.651, respectively. The mean of $PeerLoss \times SameEthnicity$ is 0.015 for atypical tasks and 0.023 for typical tasks. All columns include worker, team, and year fixed effects. Standard errors are clustered at the team level ($p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

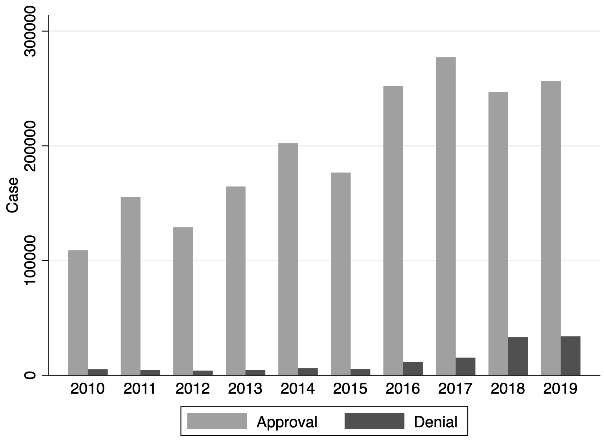
Table 8: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING BY POSITION

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 (%) × Same ethnicity		-0.017*		0.035
		(0.009)		(0.022)
Loss of seniors (%) × Same ethnicity		-0.040*		0.005
		(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

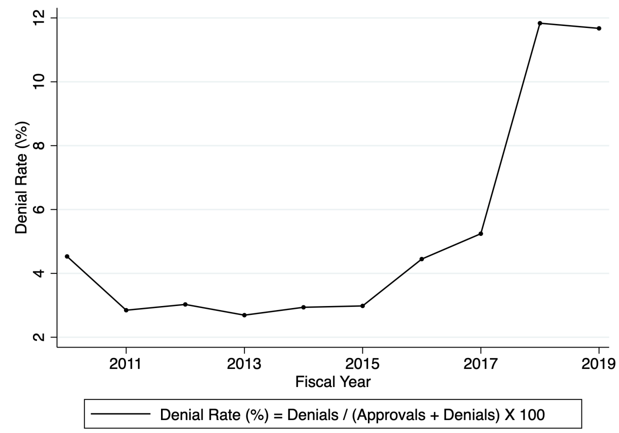
Notes: This table reports the coefficient estimates of the regressions shown in equations 1 and 2 using a balanced panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed (for the 2014–2018 period). The sample is partitioned into two subsamples based on position. We consider entry-level employees and software engineers as juniors, and team leaders and above as seniors. The dependent variable is the performance rating per year per person. The treatment variable is the percentage of junior ($Loss of Juniors(\%)$) or senior ($Loss of Seniors(\%)$) 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. The mean of PeerLoss for Junior and Senior workers is 0.652 and 0.580, respectively. The mean of $PeerLoss \times SameEthnicity$ is 0.019 for Junior workers and 0.017 for Senior workers. All columns include worker, team, and year fixed effects. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Appendix Figures and Tables

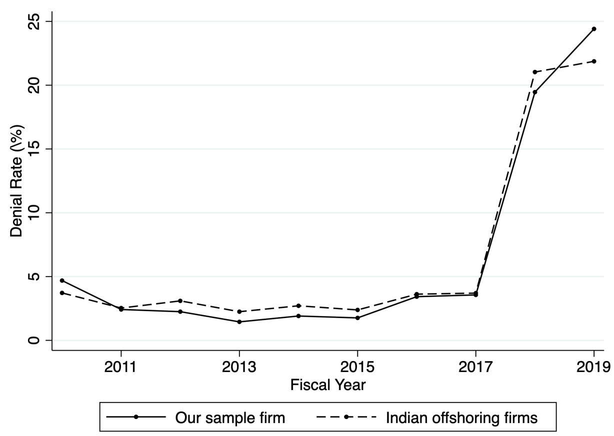
Figure A.1: H-1B VISA EXTENSION APPROVALS AND DENIALS FROM ADMINISTRATIVE DATA (FISCAL YEARS)



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



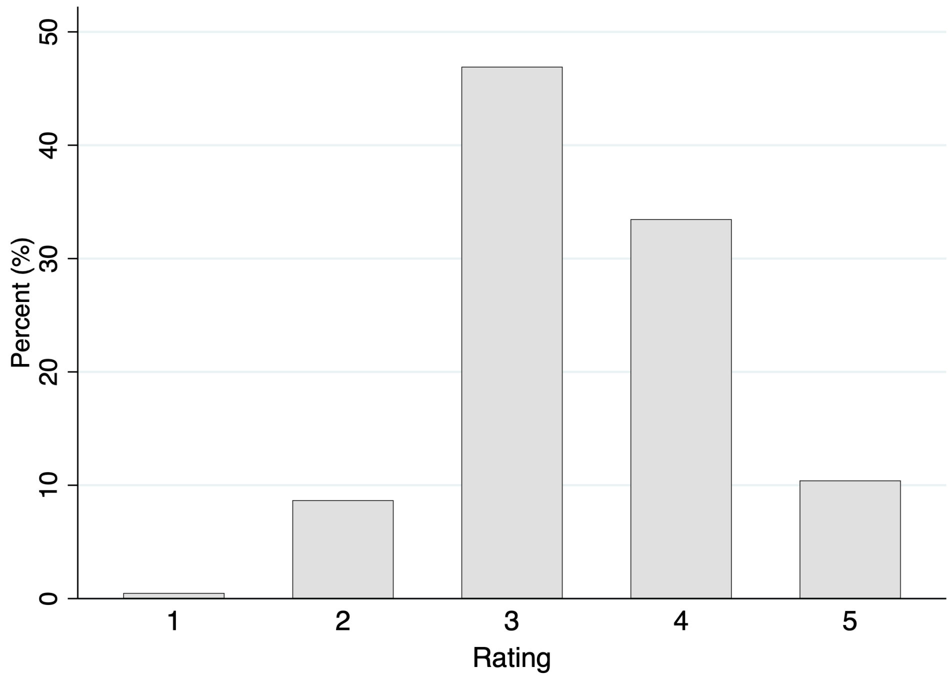
(b) Visa-Extension Denial Rate (all firms)



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

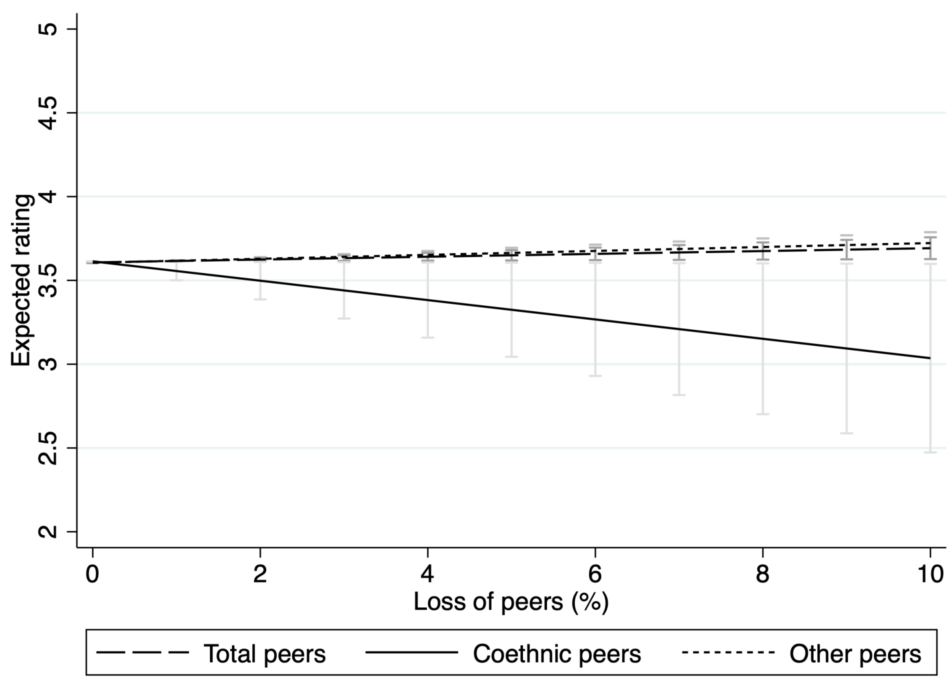
Notes: Figures (a) and (b) present data about all petitions filed with USCIS requesting an extension of existing H-1B visas (primarily for existing employees at the same company) from the USCIS H-1B Employer Data Hub. These data include all the visa extensions filed in the United States, for all employers. 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



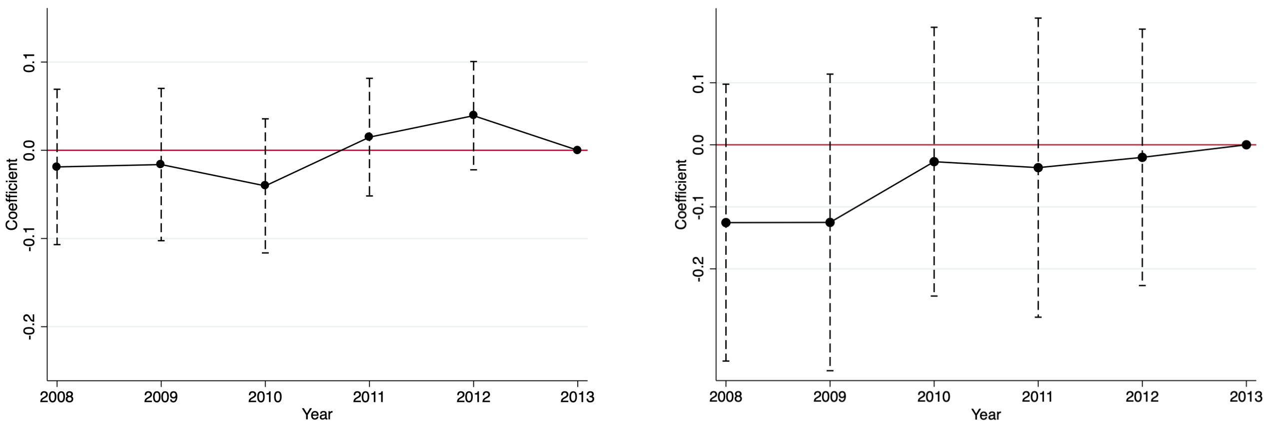
Note: This histogram presents the percentage of average employee ratings, by whole number.

Figure A.3: 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 A.4: BASELINE INDIVIDUAL RATINGS BY STATUS, 2008–2013

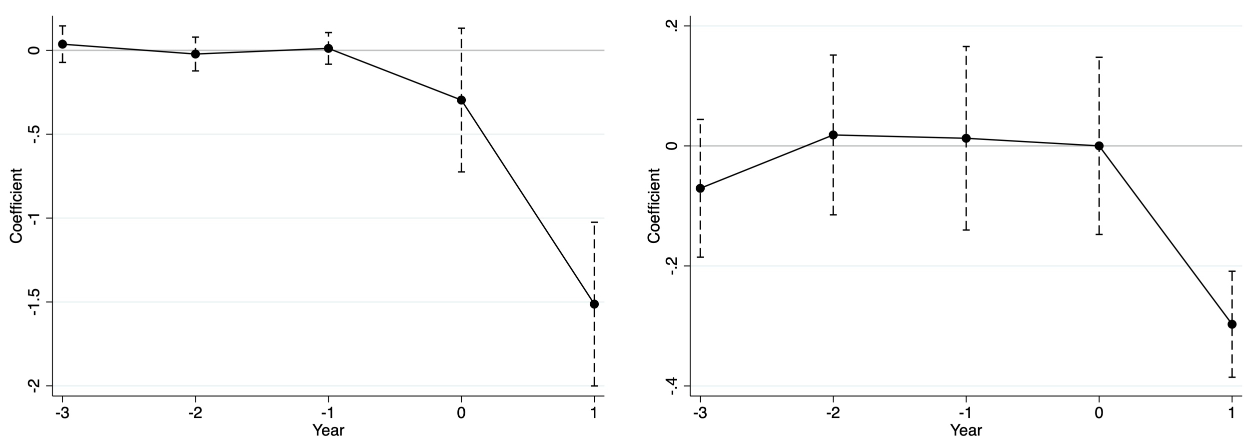


(a) Visa Status of Peers, Coefficient

(b) Visa Status, Coefficient

Notes: The figures present pretrends for our main outcome, i.e., individual 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) presents the coefficient estimates of the regression in equation 3. Plot (b) shows coefficient estimates of the ratings of employees whose visa extension was denied versus employees whose visa extension was approved. In all plots, we show 95% confidence intervals.

Figure A.5: STAGGERED DIFFERENCE-IN-DIFFERENCES (BALANCED SAMPLE)

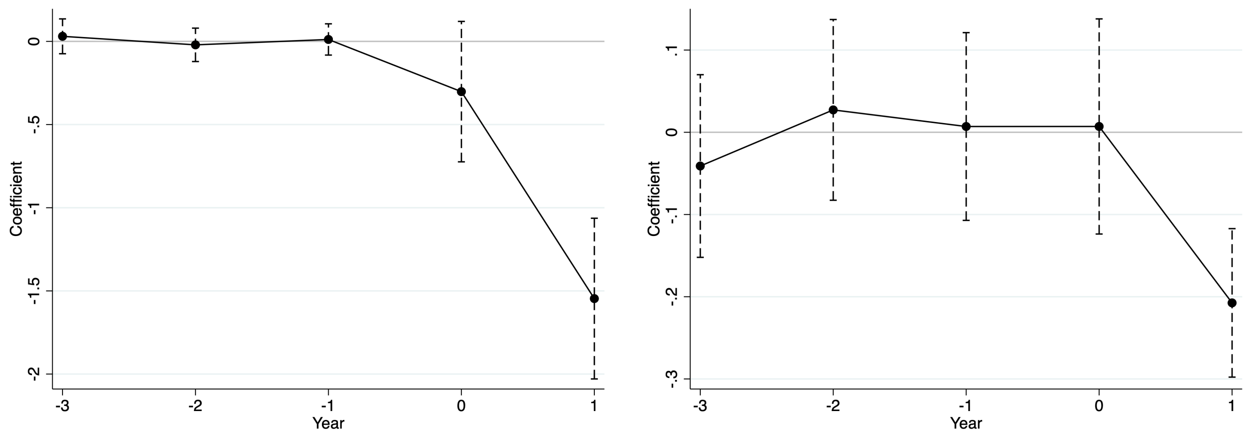


(a) Callaway and Sant'Anna (2021)

(b) Chaisemartin and D'Haultfœuille (2022)

Notes: Plot (a) shows coefficients on the loss of coethnic peers from Callaway and Sant'Anna (2021). Estimators from De Chaisemartin and d'Haultfoeuille (2024) are shown in plot (b). We use a balanced panel and 95% confidence intervals.

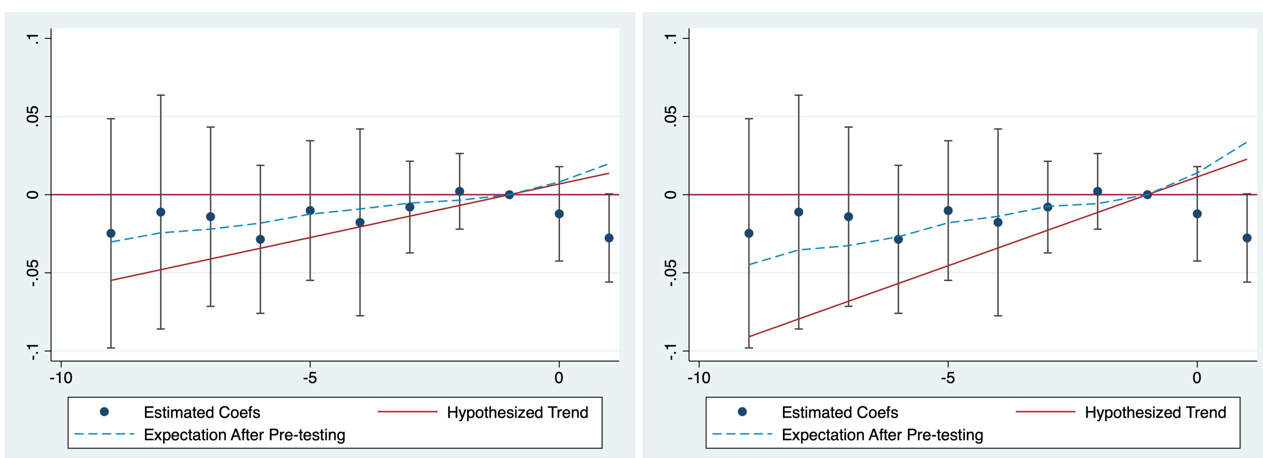
Figure A.6: STAGGERED DIFFERENCE-IN-DIFFERENCES (UNBALANCED SAMPLE)



(a) Callaway and Sant'Anna (2021) (b) Chaisemartin and D'Haultfœuille (2022)

Notes: Plot (a) shows coefficients on the loss of coethnic peers from Callaway and Sant'Anna (2021). Estimators from De Chaisemartin and d'Haultfoeuille (2024) are shown in plot (b). We use an unbalanced panel and 95% confidence intervals.

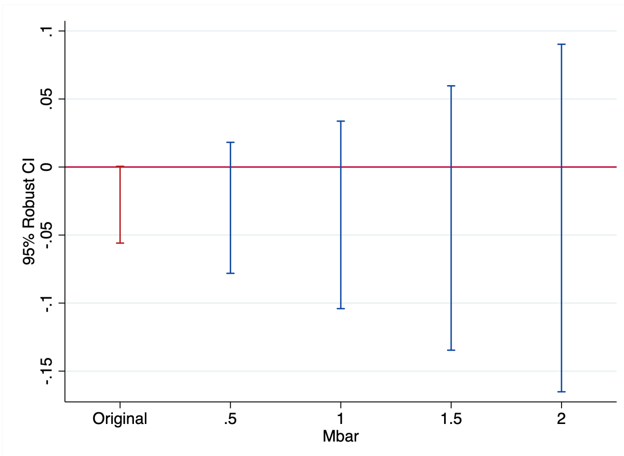
Figure A.7: PRE-TRENDS



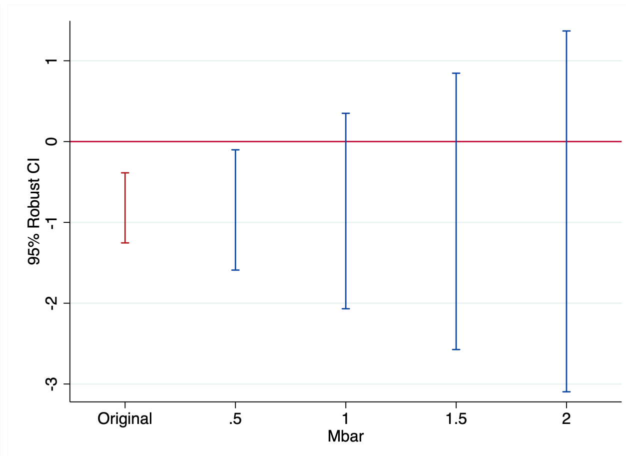
(a) Power 0.5 (b) Power 0.8

Notes: The figures show parallel trends with slope suggested by Roth (2022). Plots (a) and (b) utilize a power threshold of 50% and 80%, respectively.

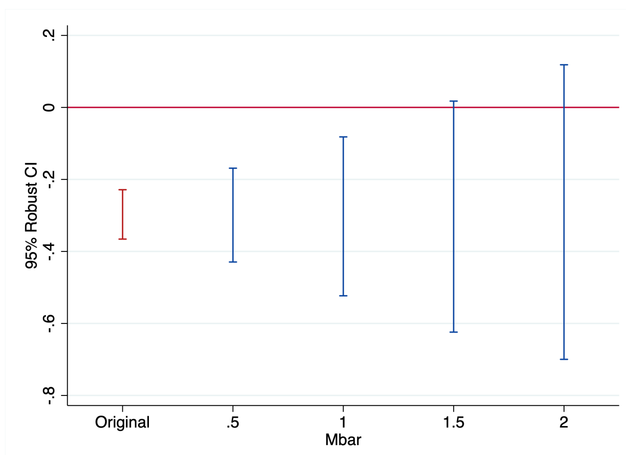
Figure A.8: SENSITIVITY ANALYSIS USING HONEST DID



(a) Honest DiD



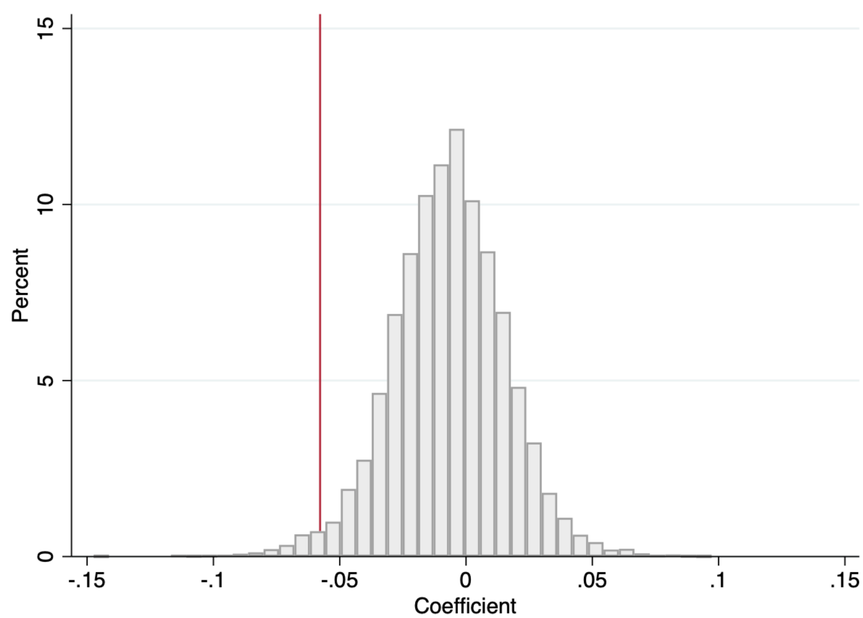
(b) Honest DiD with CS(2021)



(c) Honest DiD with DS(2022)

Notes: The figures show sensitivity analysis using the HonestDiD approach from Rambachan and Roth (2023). Plot (a) employs a TWFE(Two-Way Fixed Effects) DD method, while plots (b) and (c) utilize the DD approaches from Callaway and Sant'Anna (2021), and Chaisemartin and D'Haultfœuille (2022), respectively.

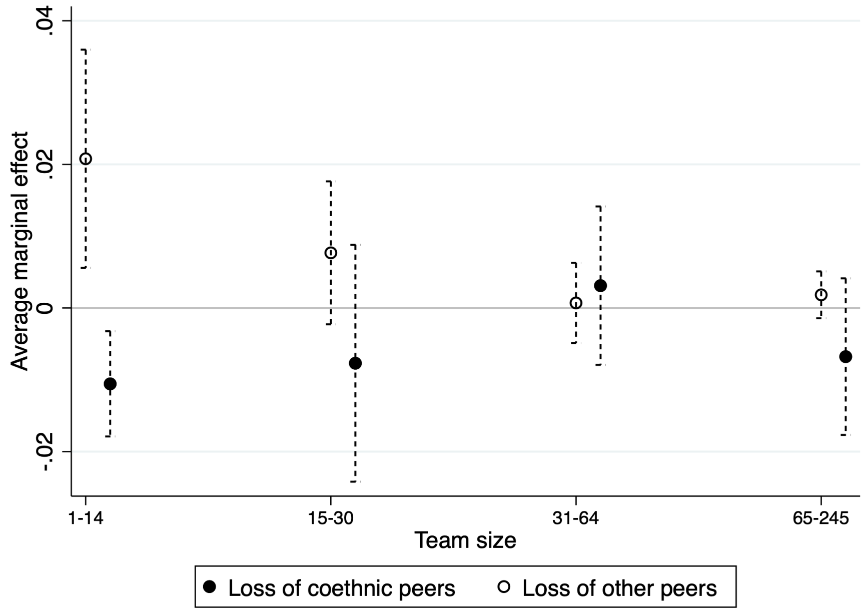
Figure A.9: PLACEBO TEST



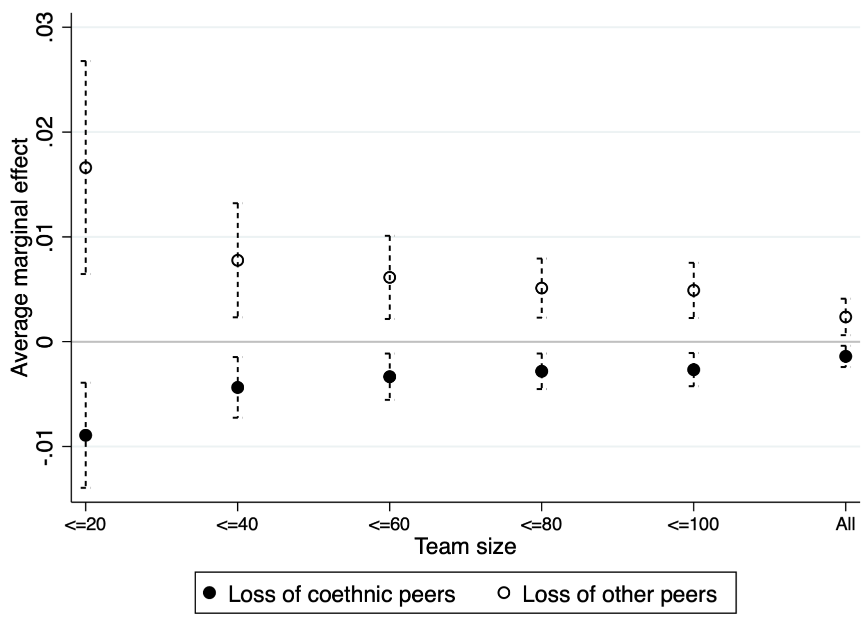
Notes: This figure plots the coefficient estimates of a placebo treatment test. There are 283 employees in our sample whose visa extension was denied. To perform this placebo test, we randomly chose 283 employees, without replacement, and constructed the placebo treatment for the loss of the same-ethnicity 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 ($p < .001$).

Figure A.10: AVERAGE MARGINAL EFFECT BY TEAM SIZE

(a) Team size (four subgroups)



(b) Maximum team size



Notes: The figures show 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: 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 shows 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 the 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 A.2: 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.3: NUMBER OF TEAMS THAT LOST A PEER BY TEAM SIZE

Team Size (1)	Frequency (2)	Percent (3)
1	3	2.21
2	4	2.94
3	1	0.74
4	2	1.47
5	2	1.47
6	2	1.47
7	3	2.21
8	7	5.15
9	5	3.68
10	3	2.21
11	3	2.21
12	1	0.74
13	1	0.74
14	3	2.21
15	4	2.94
16	4	2.94
17	3	2.21
18	6	4.41
19	3	2.21
20	4	2.94
21	4	2.94
22	3	2.21
23	2	1.47
24	1	0.74
25	2	1.47
26	3	2.21
27	3	2.21
28	2	1.47
29	2	1.47
30	4	2.94
34	2	1.47
35	5	3.68
36	4	2.94
37	1	0.74
40	2	1.47
41	1	0.74
42	1	0.74
43	1	0.74
44	1	0.74
48	1	0.74
50	3	2.21
51	2	1.47
54	1	0.74
55	1	0.74
59	1	0.74
60	1	0.74
61	2	1.47
63	1	0.74
64	1	0.74
65	1	0.74
68	2	1.47
69	1	0.74
70	1	0.74
71	1	0.74
77	1	0.74
84	1	0.74
90	1	0.74
149	1	0.74
154	1	0.74
165	1	0.74
171	1	0.74
245	1	0.74

Notes: The table shows the number of teams that experience the loss of a team member by team size.

Table A.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	Loss of Co-Ethnic Peers (Percent)
No loss of peers	2504	0	2504	0
Loss of peers	1203	2783	3986	69.82
Total	3707	2783	6490	42.9

Panel B: By number of co-ethnic peers lost

Loss of peers	Loss of co-ethnic peer: **0**	**1**	**2**	**3**	**4**	**5**	**6**	**9**	**Total**
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 A.5: NUMBER OF TEAMS THAT LOST A PEER BY TEAM SIZE

Team Size (1)	Frequency (2)	Percent (3)	Loss Peers (4)	Loss Coethics (5)
1	3	2.21	0.009	0.009
2	4	2.94	0.016	0.008
3	1	0.74	0.006	0.002
4	2	1.47	0.015	0.004
5	2	1.47	0.010	0.002
6	2	1.47	0.022	0.004
7	3	2.21	0.039	0.006
8	7	5.15	0.035	0.004
9	5	3.68	0.042	0.005
10	3	2.21	0.027	0.003
11	3	2.21	0.039	0.004
12	1	0.74	0.010	0.001
13	1	0.74	0.009	0.001
14	3	2.21	0.031	0.002
15	4	2.94	0.053	0.004
16	4	2.94	0.028	0.002
17	3	2.21	0.035	0.002
18	6	4.41	0.056	0.003
19	3	2.21	0.053	0.003
20	4	2.94	0.040	0.002
21	4	2.94	0.048	0.002
22	3	2.21	0.057	0.003
23	2	1.47	0.043	0.002
24	1	0.74	0.021	0.000
25	2	1.47	0.040	0.001
26	3	2.21	0.023	0.001
27	3	2.21	0.049	0.001
28	2	1.47	0.036	0.001
29	2	1.47	0.086	0.002
30	4	2.94	0.050	0.001
31	0	0.00	0.000	0.000
33	0	0.00	0.000	0.000
34	2	1.47	0.020	0.001
35	5	3.68	0.040	0.001
36	4	2.94	0.042	0.001
37	1	0.74	0.041	0.001
40	2	1.47	0.050	0.001
41	1	0.74	0.024	0.001
42	1	0.74	0.024	0.001
43	1	0.74	0.035	0.001
44	1	0.74	0.045	0.001
48	1	0.74	0.021	0.000
50	3	2.21	0.033	0.001
51	2	1.47	0.059	0.001
54	1	0.74	0.019	0.000
55	1	0.74	0.036	0.000
59	1	0.74	0.034	0.000
60	1	0.74	0.067	0.001
61	2	1.47	0.033	0.000
63	1	0.74	0.063	0.001
64	1	0.74	0.016	0.000
65	1	0.74	0.062	0.000
68	2	1.47	0.044	0.000
69	1	0.74	0.014	0.000
70	1	0.74	0.014	0.000
71	1	0.74	0.042	0.000
75	0	0.00	0.000	0.000
77	1	0.74	0.026	0.000
84	1	0.74	0.024	0.000
90	1	0.74	0.011	0.000
149	1	0.74	0.020	0.000
154	1	0.74	0.032	0.000
165	1	0.74	0.030	0.000
171	1	0.74	0.053	0.000
245	1	0.74	0.029	0.000

Notes: The table shows the number of teams that experience the loss of a team member by team size.

Table A.6: 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 shows baseline characteristics of individuals who filed for a visa extension. Column 2 shows the 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.7: 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	-0.003**	-0.002	-0.003**	-0.002
× Same ethnicity	(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: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.8: 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 business-unit level. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A.9: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS, DUMMY TREATMENT WHILE CONTROLLING FOR TEAM SIZE AND COUNT OF PEERS LOST AS TREATMENT

Sample (Year)	Balanced (2014-2018)		Unbalanced (2008-2018)	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
A. Dummy treatment: any loss in peers				
PeerLoss	0.054**	0.092***	0.043*	0.077**
	(0.025)	(0.033)	(0.024)	(0.030)
PeerLoss × Same ethnicity	-	-0.064*	-	-0.057
		(0.035)		(0.035)
B. Count treatment: the number of peers lost				
PeerLoss	-0.000	0.022*	-0.002	0.020*
	(0.007)	(0.013)	(0.006)	(0.011)
PeerLoss × Same ethnicity	-	-0.049**	-	-0.048**
		(0.024)		(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	42,390	42,384
R-squared	0.049	0.049	0.084	0.084

Notes: The treatment variable is a dummy variable indicating the loss of at least one peer in Panel A, while a count variable measuring the number of peers lost is used in Panel B. We account for team size at the project team level (dropping our usual team fixed effects), and include the business unit fixed effects. Standard errors are clustered at team level. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.10: 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 the 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.11: 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 × Other ethnicity	-	-0.008	-	0.027
		(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 the 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.12: 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 × Same ethnicity	-0.079*	-0.068**	-0.079***	-0.067*
	(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 the rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied. Column 1 excludes 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 includes 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.13: 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 × Same ethnicity	-	-0.029	-	-0.048*
		(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 the 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.14: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS, STATES

Sample (Year)	Balanced (2014-2018)		Unbalanced (2008-2018)	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss	0.008**	0.009**	0.007*	0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
PeerLoss × Same ethnicity	-	-0.029	-	-0.053*
		(0.023)		(0.030)
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	41,720	41,720
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. In all columns, co-ethnicity is being measured using employees' 26 birth states. The dependent variable is the 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 a balanced panel that has 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 based on their state of birth. Standard errors are clustered at team level. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.15: CULTURAL ZONES OF INDIA

Zone (1)	Zonal Centre (2)	Extent (3)
North Culture Zone	North Zone Cultural Centre, Patiala, Punjab	Chandigarh, Haryana, Himachal Pradesh, Jammu and Kashmir, Ladakh, Punjab, Rajasthan, Uttarakhand
North Central Culture Zone	North-Central Zone Cultural Centre, Allahabad, Uttar Pradesh	Bihar, Delhi, Haryana, Madhya Pradesh, Rajasthan, Uttar Pradesh, Uttarakhand
East Culture Zone	East Zone Cultural Centre, Kolkata, West Bengal	Andaman and Nicobar Islands, Assam, Bihar, Jharkhand, Manipur, Odisha, Sikkim, Tripura, West Bengal
North East Culture Zone	North East Zone Cultural Centre, Chümoukedima, Nagaland	Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, Tripura
South Culture Zone	South Zone Cultural Centre, Thanjavur, Tamil Nadu	Andaman and Nicobar Islands, Andhra Pradesh, Karnataka, Kerala, Lakshadweep, Puducherry, Tamil Nadu, Telangana
South Central Culture Zone	South-Central Zone Cultural Centre, Nagpur, Maharashtra	Andhra Pradesh, Chhattisgarh, Goa, Karnataka, Madhya Pradesh, Maharashtra, Telangana
West Culture Zone	West Zone Cultural Centre, Udaipur, Rajasthan	Dadra and Nagar Haveli and Daman and Diu, Goa, Gujarat, Maharashtra, Rajasthan

Notes: The Cultural Zones of India are seven overlapping zones designed by the Ministry of Culture of the Government of India.

Table A.16: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS, CULTURAL ZONES

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*	0.012***
	(0.004)	(0.004)	(0.004)	(0.005)
PeerLoss × Same ethnicity	-	-0.070**	-	-0.086***
		(0.032)		(0.027)
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	41,720	41,720
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. Co-ethnicity in all columns is defined using the 7 Cultural Zones of India. The dependent variable is the 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 a balanced panel that has 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 based on cultural zones of India. Standard errors are clustered at team level. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.17: EFFECT OF LOSING TEAM MEMBERS ON INDIVIDUAL RATING BY 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 the 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.18: 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 the 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.19: 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.20: 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.21: 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 × Same ethnicity	-	-0.073***	-	-0.054**
		(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.22: 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 × Same ethnicity	-	-0.056**	-	-0.071***
		(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 the 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 a 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.23: 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 the performance rating per year per person. The treatment variable is the percentage of junior (*Loss of Juniors* (%)) or senior (*Loss of Seniors* (%)) 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.24: 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.25: 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 the 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. The mean of PeerLoss for small and large teams is 0.443 and 0.767, respectively. The mean of $PeerLoss \times SameEthnicity$ is 0.021 for small teams and 0.015 for large teams. Standard errors are clustered at the team level ($p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A.26: BASELINE REGRESSION USING VARIOUS DEFINITIONS OF TEAM SIZE

A. Small teams defined using different percentiles

	Small teams (<=25th percentile, <=10 team members)	Small teams (<=30th percentile, <=13 team members)	Small teams (<=40th percentile, <=20 team members)	Small teams (<=60th percentile, ¡= 36 team members)	Small teams (<=70th percentile, <=51 team members)	Small teams (<=75th percentile, <=63 team members)
	(1)	(2)	(3)	(4)	(5)	(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)***
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)***
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)	Large teams (>30th percentile, >13 team members)	Large teams (>40th percentile, >20 team members)	Large teams (>60th percentile, >36 team members)	Large teams (>70th percentile, >51 team members)	Large teams (>75th percentile, >63 team members)
	(1)	(2)	(3)	(4)	(5)	(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)
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)
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 the 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: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.27: 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 × Same ethnicity	-	-0.069***	-	-0.103
		(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 the 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. The mean of PeerLoss for low- and high-diversity teams is 0.555 and 0.678, respectively. The mean of $PeerLoss \times SameEthnicity$ is 0.021 for low-diversity teams and 0.015 for highly diverse teams. All columns include worker, team, and year fixed effects. Standard errors are clustered at the team level ($p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A.28: 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 the 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. The mean of PeerLoss for young and old workers is 0.572 and 0.664, respectively. The mean of $PeerLoss \times SameEthnicity$ is 0.017 for young workers and 0.019 for old workers. All columns include worker, team, and year fixed effects. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A.29: 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. The mean of PeerLoss for male and female workers is 0.613 and 0.646, respectively. The mean of $PeerLoss \times SameEthnicity$ is 0.018 for males and 0.015 for females. All columns include worker, team, and year fixed effects. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A.30: 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 ($91,861). The dependent variable is the performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied (x 100) ($PeerLoss$). Column 2 shows the results for the loss of the same-ethnicity peers using the regression in equation 2. The mean of PeerLoss for workers with a low and a high salary is 0.653 and 0.574, respectively. The mean of $PeerLoss \times SameEthnicity$ is 0.019 for workers with a low salary and 0.016 for workers with a high salary. All columns include worker, team, and year fixed effects. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A.31: EFFECT OF LOSING TEAM MEMBERS AND THE QUALITY OF PEERS

Sample	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 the 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 A.32: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS BY TYPE OF TASK, INTERACTION TERM

Sample (Year)	Balanced (2014-2018)		Unbalanced (2008-2018)	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss	0.006	0.009	0.005	0.009
	(0.004)	(0.006)	(0.005)	(0.006)
PeerLoss × Same ethnicity	-	-0.033	-	-0.058**
		(0.027)		(0.026)
PeerLoss × Atypical Tasks	-0.003	0.006	-0.004	0.001
	(0.007)	(0.010)	(0.007)	(0.010)
PeerLoss × Same ethnicity × Atypical Tasks	-	-0.273**	-	-0.248*
		(0.120)		(0.141)
Mean of outcome	3.592	3.592	3.423	3.423
Number of individuals	3,120	3,120	5,846	5,846
Number of units	360	360	665	665
Observations	15,600	15,600	37,508	37,502
R-squared	0.505	0.505	0.413	0.413

Notes: This table reports the coefficient estimates of the regression in equations 1 and 2 using a triple interaction model considering a dummy indicating atypical tasks. The dependent variable is the 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 A.33: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS BY POSITION, INTERACTION TERM

Sample (Year)	Balanced (2014-2018)		Unbalanced (2008-2018)	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
LossJunior	0.019**	0.005	0.021***	0.007
	(0.007)	(0.009)	(0.007)	(0.010)
LossSenior	0.001	-0.001	0.001	-0.001
	(0.007)	(0.008)	(0.008)	(0.010)
LossJunior × Same ethnicity	-	0.034	-	0.032
		(0.022)		(0.020)
LossSenior × Same ethnicity	-	0.005	-	0.005
		(0.012)		(0.012)
LossJunior	-0.008	0.015	-0.015*	0.009
× Junior	(0.009)	(0.012)	(0.008)	(0.013)
LossSenior	0.005	0.029*	0.003	0.031**
× Junior	(0.010)	(0.015)	(0.010)	(0.015)
LossJunior × Same ethnicity	-	-0.050**	-	-0.050**
× Junior		(0.023)		(0.021)
LossSenior × Same ethnicity	-	-0.046*	-	-0.055***
× Junior		(0.025)		(0.021)
Mean of outcome	3.612	3.612	3.435	3.435
Number of individuals	3,315	3,315	6,299	6,299
Number of units	418	418	812	812
Observations	16,575	16,575	40,267	40,267
R-squared	0.499	0.500	0.414	0.414

Notes: This table reports the coefficient estimates of the regression in equations 1 and 2 using a triple interaction model considering a dummy indicating junior workers (i.e., entry-level employees and software engineers). The dependent variable is the 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 A.34: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS BY TEAM SIZE, INTERACTION TERM

Sample (Year)	Balanced (2014-2018)		Unbalanced (2008-2018)	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss	0.006	0.004	0.009	0.008
	(0.007)	(0.010)	(0.007)	(0.010)
PeerLoss × Same ethnicity	-	0.077	-	0.036
		(0.187)		(0.311)
PeerLoss × Small team	0.003	0.009	-0.003	0.004
	(0.008)	(0.011)	(0.008)	(0.011)
PeerLoss × Same ethnicity × Small team	-	-0.137	-	-0.120
		(0.189)		(0.311)
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	41,720	41,714
R-squared	0.500	0.500	0.413	0.413

Notes: This table reports the coefficient estimates of the regression in equations 1 and 2 using a triple interaction model considering a dummy indicating small teams. The dependent variable is the 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 A.35: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS BY ETHNIC DIVERSITY, INTERACTION TERM

Sample (Year)	Balanced (2014-2018)		Unbalanced (2008-2018)	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss	0.003 (0.006)	0.007 (0.007)	0.002 (0.006)	0.004 (0.007)
PeerLoss × Same ethnicity	-	-0.102 (0.102)	-	-0.047 (0.127)
PeerLoss × Low diverse team	0.009 (0.007)	0.010 (0.009)	0.009 (0.007)	0.014 (0.009)
PeerLoss × Same ethnicity × Low diverse team	-	0.031 (0.105)	-	-0.049 (0.128)
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	41,720	41,714
R-squared	0.500	0.500	0.413	0.413

Notes: This table reports the coefficient estimates of the regression in equations 1 and 2 using a triple interaction model considering a dummy indicating low ethnic diversity. The dependent variable is the 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 A.36: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS BY AGE, INTERACTION TERM

Sample (Year)	Balanced (2014-2018)		Unbalanced (2008-2018)	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss	0.008**	0.011**	0.013***	0.018***
	(0.004)	(0.005)	(0.004)	(0.005)
PeerLoss × Same ethnicity	-	-0.045	-	-0.100***
		(0.029)		(0.028)
PeerLoss × Young	0.001	0.003	-0.014**	-0.020**
	(0.006)	(0.008)	(0.007)	(0.008)
PeerLoss × Same ethnicity × Young	-	-0.047	-	0.107*
		(0.073)		(0.057)
Mean of outcome	3.610	3.610	3.435	3.435
Number of individuals	3,448	3,448	6,492	6,492
Number of units	430	430	836	836
Observations	17,240	17,240	41,720	41,714
R-squared	0.500	0.500	0.413	0.413

Notes: This table reports the coefficient estimates of the regression in equations 1 and 2 using a triple interaction model considering a dummy indicating young workers (33 years old or less). The dependent variable is the 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 A.37: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS BY GENDER, INTERACTION TERM

Sample (Year)	Balanced (2014-2018)		Unbalanced (2008-2018)	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss	0.016	0.030**	0.019*	0.038***
	(0.011)	(0.013)	(0.010)	(0.012)
PeerLoss × Same ethnicity	-	-0.479*	-	-0.631**
		(0.273)		(0.299)
PeerLoss × Male	-0.008	-0.019	-0.013	-0.028**
	(0.012)	(0.014)	(0.010)	(0.012)
PeerLoss × Same ethnicity × Male	-	0.428	-	0.568*
		(0.275)		(0.298)
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	41,720	41,714
R-squared	0.500	0.500	0.413	0.413

Notes: This table reports the coefficient estimates of the regression in equations 1 and 2 using a triple interaction model considering a dummy indicating gender (male). The dependent variable is the 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 A.38: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS BY SALARY, INTERACTION TERM

Sample (Year)	Balanced (2014-2018)		Unbalanced (2008-2018)	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss	0.007 (0.005)	0.009* (0.006)	0.007 (0.005)	0.010* (0.006)
PeerLoss × Same ethnicity	-	-0.048 (0.046)	-	-0.048 (0.039)
PeerLoss × Low salary	0.004 (0.007)	0.006 (0.008)	-0.000 (0.006)	0.004 (0.008)
PeerLoss × Same ethnicity × Low salary	-	-0.027 (0.052)	-	-0.047 (0.048)
Mean of outcome	3.612	3.612	3.436	3.436
Number of individuals	3,310	3,310	6,291	6,291
Number of units	418	418	810	810
Observations	16,550	16,550	40,202	40,198
R-squared	0.499	0.499	0.414	0.414

Notes: This table reports the coefficient estimates of the regression in equations 1 and 2 using a triple interaction model considering a dummy indicating low salary. The dependent variable is the 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 (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).