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

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Abstract

We study how restrictive immigration policies and the unexpected loss of peers affect the performance of skilled migrants exploiting the unexpectedly increased denials of extensions of H-1B visas in the United States beginning in 2017. Losing a peer increased the individual performance of workers left behind, providing evidence of the law of diminishing returns. However, we find that individuals who lost peers of the same ethnic background experience a substantial decrease in performance. To resolve the endogeneity surrounding visa-denial decisions, we build an instrumental variable that exploits the fixed duration of the visas. Our mechanism test suggests that ethnic ties boost individual performance through preferential channels of knowledge and information spillovers.

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"Since software construction is inherently a systems effort—an exercise in complex interrelationships—communication effort is great, and it quickly dominates the decrease in individual task time brought about by partitioning. Adding more men then lengthens, not shortens, the schedule."

Fred Brooks, *The Mythical Man-Month*

1 Introduction

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

Nonetheless, several developed countries have in recent years embraced more-restrictive immigration regulations, making it harder for skilled migrants to work in host countries (Rissing & Castilla, 2014; Choudhury, 2021). One of the most prominent examples of this is the Trump administration's adoption 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

[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.

met with concern by many U.S. technology company CEOs, who were worried both about the negative consequences of losing foreign workers already employed at their companies and about their firms' inability to attract new high-skilled workers.[2]

While prior literature has found evidence of a negative connection between more-restrictive immigration policies and several economic outcomes at the regional level (e.g., Kerr & Lincoln, 2010a; Clemens, 2011) and at the firm level (e.g., Bahar et al., 2020), it is unclear how stricter immigration policies influence individual worker performance within firms. On one hand, given the well-established tendencies of diminishing marginal product (Clark, 1888; Clark, 1889) and hiring on the margin (Brooks Jr, 1974), the effect of losing a peer on workers who remain at the firm could be very small, or even positive. On the other hand, given the potential for knowledge spillovers in highly skilled workplaces, the effect of losing a peer on other workers could be large and negative. Understanding these effects within firms will be important for managers who need to adjust workplace composition and policies on the fly in the midst of ever-increasing immigration restrictions.

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

In general, answering this question is challenging because of the inherent endogeneity of peer departure and the scarcity of detailed individual-level data within firms. In this paper, we overcome these obstacles by combining individual-level microdata and an unexpected change in immigration policies to show how exogenous changes in worker composition affect individual workers' performance within teams. We use data from a large Indian technology

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

firm that employs around 150,000 workers globally, serving clients in multiple countries. We focus on Indian workers located in the United States, and we exploit different subethnicities within India to shed light on the role of ethnicity on peer performance. In 2017 and 2018, the United States unexpectedly began denying requests to extend temporary work visas (H-1B visas) at an unprecedented level.[3] Teams composed of H-1B visa workers began suddenly losing members.[4] By leveraging our detailed data at the individual and team levels combined with an objective measure of performance, we shed light on the consequences of the loss of a peer on individual performance within teams. Most important, by comparing individuals who lost peers of similar ethnicity to those who lost ethnically dissimilar peers, we investigate how ethnic ties moderate the relationship between stricter immigration policies and individual performance.

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

Our results highlight how, on average, stricter immigration policies resulting in the loss of a peer increase the individual performance of those left behind, consistent with the law of diminishing marginal product (Brooks Jr, 1974). However, for the first time, we document an important boundary condition to this effect: the effect is reversed when losing a team member of the same ethnicity. In other words, same-ethnicity peers tend to increase each

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

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

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

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

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

[5] We define *performance rating* in Section 3, paragraph 2.

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

This paper contributes to research on productivity of skilled workers within firms, especially within streams of literature in skilled migration, ethnic ties and loss of peers. First, it is connected to studies examining the effects of tighter immigration policies and visa regulations on a variety of economic outcomes at different levels, especially those exploiting the changes of the H-1B visa program (e.g., Kerr and Lincoln (2010b)). We contribute to this literature by studying 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 outcomes (e.g., Hernandez (2014), Kulchina and Hernandez (2016)). Our work also speaks to the literature examining the role of ethnic diversity within firms and teams on performance (e.g., Lang, 1986; Freeman & Huang, 2014; Hjort, 2014; Choudhury & Kim, 2019; Marx et al., 2021) by exploring how different characteristics of teams and tasks moderate the relationship. Finally, our paper is related to a growing literature examining the effects of an unexpected loss of peers on the performance of the workers left behind (e.g., Borjas & Doran, 2012; Waldinger, 2012; Azoulay et al., 2019).

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

2 Conceptual Framework and the H-1B Visa Program

The loss of a peer may have significant consequences on the performances of workers left behind. One prominent theory in the economics and management literature, the law of diminishing marginal returns, predicts that the loss of a worker might not decrease peers' performance and might actually be beneficial. This phenomenon, documented by the landmark work of Fred Brooks in *The Mythical Man-Month* (Brooks Jr, 1974), is based on Brooks' observation that assigning additional workforce to a project did not increase the team's overall performance and oftentimes was associated with an increase in lead time. In general, similar results have emerged in a variety of contexts and settings. For instance, the arrival of Soviet mathematicians in the United States after the collapse of the Soviet Union decreased the productivity of U.S. mathematicians working in the same fields (Borjas & Doran, 2012). Similarly, when investigating the consequences of the death of prominent scientists on the performance of other researchers, Azoulay et al. (2019) find that aside from immediate collaborators, other scientists experienced a surge in the number of publications and grants received. When looking at the performance of peers after the dismissal of high-quality scientists in Nazi Germany, Waldinger (2012) do not observe a decrease in peers' performance.

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

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

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

We try to investigate which mechanisms are at play in our setting by exploiting a tightening of immigration policies that resulted in an unexpected increase in H-1B visa extension denials. 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. The number of visas is subject to an annual quota, and the cap has generally been met every year. 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. Because the annual number of H-1B visa slots is limited, 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."[6]

In general, the documentation for extending an H-1B visa is similar to that required when applying for a new H-1B, making the extension process costly and demanding. The petitioning employer has to meet strict requirements[7] and has to prove that the employee is qualified for a specialty occupation.[8] The timing of visa extensions is also strictly regulated: applicants are allowed to petition for an extension only during the six months leading up to the H-1B expiration date.

H-1B visa extensions can be rejected for several reasons, and denials are common. That said, the number of H-1B visa extension denials unexpectedly surged after Donald Trump signed the "Buy American and Hire American" executive order on April 18, 2017, which pushed the USCIS to deny more H-1B petitions in the name of protecting domestic workers. Panel B of Figure A.1 in the Appendix shows the denial rate of H-1B extensions over time. Rejections

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

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

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

more than doubled in fiscal 2018 (October 2017 to September 2018). Firms that depended on H-1B workers faced a sudden decrease in their labor force. 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).

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

3 Data and Methods

3.1 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, serving clients in numerous countries, including the United States, where it established a subsidiary in Silicon Valley in the late 1980s. This organization is the focus of our analysis. 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. We then constructed panel data related to their performance ratings and to denials of the H-1B visa extensions at the employee-year level. In our sample, applications, approvals, and denials of the H-1B visa extensions started in 2014, then denials surged during the Trump administration. Figure 1 shows the trend in denials of the H-1B visa extensions in our sample. 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 objective measurement based on criteria such as client satisfaction, ability to meet deadlines, and number of tasks completed, rather than on subjective evaluation by their supervisors. Figure 2 plots histograms of the average ratings in our data at the individual level and at the team-project level.

Characteristics of employees 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 a similar culture and language. By employing this geographical-based classification to identify employees' ethnicities, we obtain five main possible ethnicities (i.e., North, South, West, East, and Northeast India) Our results are robust to the use of other measures, such as a language-based classification. Table A.1 shows some summary statistics related to ethnicities while outlining our main categories. The geographical extent and historical background of India are reassuring about the generalizability of our results to different contexts. The historical fragmentation and recent unification of the country have created a plethora of subcultures with their own religions, languages, and customs, all of which persist today.

Table 1 reports basic descriptive statistics for our sample, which is composed of 6,913 individuals observed from 2014 to 2018. The average individual employee rating is 3.4 (minimum of 1, maximum of 5).[9] In general, ratings are normally distributed, with employees most of the time achieving a rating 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.[10] Employees are subdivided into 841 teams encompassing 187 business units. On average, each team has eight members. In terms of visa denials, roughly

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

[10] 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).

44% of employees needed a visa extension during the period we analyze; of these, 14% were denied. This translates to an average denial rate of 0.16% for the average team, i.e., the loss of 0.13 peers per team per year. At the business-unit level, we observe an average denial rate of 0.1%, similar to the loss of 0.37 peers per average business unit per year.

3.2 Empirical Strategy

Our empirical strategy exploits the variation in the decisions on H-1B visa extensions. We consider two facts: that the applications could be approved or denied, and that H-1B visa denials had been rising sharply during the Trump administration. We examine a sample of employees whose extension was approved or not filed and compare those who had team members whose extension was denied (loss of peers) with those who had no team members whose extension was denied (no loss of peers).

We measure the causal effect of the loss of team members on performance in a difference-in-differences framework. Specifically, we employ the following specification:

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

where Y_{it} is the rating of employee i in year t and $PeerLoss_{it}$ is the number of the H-1B extension denials in employee i's team (or business unit) divided by the number of employees on the team (or in the business unit) multiplied by 100.[11] This variable measures the loss of peers due to visa-extension denials as a percentage. We include the quartic of the age of person i in year t, the individual fixed effect γ_i, and the year fixed effect τ_t. We report the results from this estimation in Table 2, columns 1 and 3.

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

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

where $SameEthnicity_i$ indicates whether employee i and a team member whose visa exten-

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

sion was denied belong to the same-ethnicity group. The coefficient α thus examines the effect of the loss of the same-ethnicity peers due to the visa-extension denial. We report the results from this estimation in Table 2, columns 2 and 4.

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

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

where D_t is an indicator variable corresponding to a particular year t. The variable of $PeerLoss_i$ uses the total number of team members whose visa extension was denied.[12] 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.

3.3 Validity of the Identification

We investigate the validity of the identification by regressing variables that should not be affected by the result in the visa-extension denial. H-1B visa extensions, in our sample, began to be filed and approved in 2014. Thus, we examine pretrends between 2008 and 2013. Table 3 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 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 extension was filed but denied with other employees whose visa extension was filed and approved. We also find no significant differences after controlling for individual characteristics.

[12] 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 pretrends, because the visa extension denials occurred between 2016 and 2018 in our sample. $PeerLoss_{it}$ takes a value of zero before 2016.

The key identifying assumption of our difference-in-differences strategy is that the outcome of employees who had team members whose visa extension was denied and the outcome of other employees who lost no such team member does not vary in the absence of extension denials. Figure 4 shows pretrends of ratings among employees by their statuses between 2008 and 2013. We can then compare the average ratings of employees who had one or more team members whose visa extension was denied (loss of peers) with the outcome of other employees who did not lose any members. Panel A shows common pretrends based on raw data. Panel B presents coefficient estimates based on Equation 3 relative to the base year (2013): overall, no coefficients are significant for the preperiod. These tests provide evidence of the validity of our empirical strategy. We also find no difference in pretrends by comparing employees whose visa extension was denied with other employees whose visa extension was approved in Panels C and D. Overall, these findings affirm the validity of our identification strategy.

One might argue that visa denials might be correlated with time-varying and time-unvarying unobservable worker characteristics. For instance, it might be that less-skilled or less-experienced workers experience a higher rate of visa-extension denials. If this bias was at play in our context, this might result in an underestimation in the magnitude of the $PeerLoss$. This means that, if anything, our OLS coefficients would be providing conservative estimates of the effect of a loss of a member on team performance. Though the individual fixed effects in our main specification should already net out any biases derived from time-unvarying individual workers' features, there might still be some biases deriving from time-varying individual and team features.

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

Leveraging the fixed nature of visa denials, we build an instrument by considering the number of peers who filed an extension (in a given year) on team size. Formally, we estimate the following first-stage and instrumented equations:

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

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

4 Results

4.1 Denials and Peer Performance

We examine how more-stringent immigration policies resulting in the loss of team members due to the visa denials affect team members' performance. Table 2 reports the results of our difference-in-differences specification (Equation 1) using ordinary least squares (OLS). We report results using two types of samples: an unbalanced sample that considers the 2008–2018 period, where some ratings are not observed, and a balanced sample that considers the 2014–2018 period. The models using the balanced sample are our preferred specifications. The coefficient ($PeerLoss$) in column 1 suggests that the visa denials of team members on the project team increased other team members' performance. This finding suggests that a 1% loss of peers due to the visa denials at the project-team level increased ratings by 0.008. Specifically, for employees whose ratings were observed between 2014 and 2018 (in column 1), a 0.008 increase in rating was attributed to a 1% loss of peers due to the 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 leads to a 2.7% increase in performance of those left behind.

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 2 shows a negative and significant coefficient for the interaction term ($PeerLoss \times SameEthnic$). Our results suggest that a 1% loss of team members due to the visa denials decreased ratings by 0.058 (1.6%) within teams. On the average project team with eight members, losing a same-ethnicity peer decreased the performance of those left behind by 20%. Figure 6 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 3 shows the coefficients on the interaction term ($PeerLoss \times SameEthnic$) interacted for each year relative to the base year 2014 in Equation 3. This figure suggests that the negative effect on performance in our sample occurred in response to the loss of the same-ethnicity peers when the visa-extension denials surged in 2017 and 2018. The results also provide evidence on the identifying assumption of parallel trends in performance of workers who lost peers and those who did not before the visa denials surged in 2017. Panel B of Figure 3 shows the dynamic effects relative to a year before the loss of the same-ethnicity peers (where time 0 represents the year a co-worker's visa extension is denied). We find that the results are robust to this specification.

To make sure that visa denials are orthogonal to workers' and teams' time-varying characteristics, we instrument the ratio of visa denials with the instrumental variable described in Section 3.3, i.e., the share of visa extensions on team size. In general, this instrument is highly correlated with our endogenous variable: the coefficient of the first stage is 0.067 with a standard error of 0.011, which translates to a 1% significance level. Table 4 shows the results of the instrumented specification presented in Equation 4, where we instrument $PeerLoss$ and the interaction ($PeerLoss \times SameEthnic$) with the number of peers who needed to file a visa extension on team size (i.e., $FiledPeer$) and its interaction with $SameEthnic$ (i.e., $FiledPeer \times SameEthnic$). All specifications exhibit strong F-statistics, which are consistently higher than 10.

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

As a further robustness check, we run our main specification using a different outcome variable: team rating. Instead of considering individual ratings aggregated by teams, as we do in our main specification, we assess the raw data at the project-team level obtained from the company. Some basic descriptive statistics for team-level data are available in Table A.2 in the Appendix, while Figure A.3 shows the distribution of team ratings. Panel A of Table A.3 shows how our results are consistent with this alternative outcome variable.

It would be interesting to explore whether the drop in performance caused by visa denials can have pervasive consequences beyond the team level. To do so, we aggregate individual ratings at the business-unit level. Panel B of Table A.3 shows the result of these specifications. Interestingly, the loss of an employee is no longer associated with a decrease in performance. However, the loss of a co-ethnic team member still has significant and negative effects on peer performance, suggesting not only that the consequences of visa denials are experienced at the team level but also that they can have a ripple effect throughout a firm's business units. Figure A.4 in the Appendix shows the coefficient of the interaction ($PeerLoss \times SameEthnic$) over time relative to 2014 and 2013.

4.1.1 Additional Robustness Checks

Because our dependent variable is an ordered index of ratings, ranging from 1 (Needs Improvement) to 5 (Distinguished), we also employ an ordered logit model as an alternative specification. Table A.4 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 lower ratings are 1.03 times greater for workers in a project team who lost some team members than workers who did not lose any peers (column 2). However, the odds of a higher rating versus lower ratings 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 the same-ethnicity peers and the outcome variable. We exploit the fact that employees could lose peers with a different ethnicity 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.5 show the insignificant coefficients on the interaction term ($PeerLoss \times OtherEthnic$) according to the modified Equation 2. The loss of non-co-ethnic peers due to the visa denial is not sufficient to affect performance, suggesting that the loss of co-ethnic peers is key in decreasing team members' performance.

We also conduct a falsification test in which the treatment groups and treatment periods are randomly selected. In our sample, 283 employees who filed an H-1B visa extension were denied. We randomly choose 283 other employees as a placebo treatment group, without replacement, and construct a new right-hand-side variable. We then reestimate the regression in Equation 3 and report the coefficient on ($PeerLoss \times SameEthnic$) of the placebo treatment variable. We repeat this test 10,000 times with random shuffles. Figure 5 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.

4.1.2 Alternative Explanations

Ethnicity classification. We might be worried that our measure of ethnicities based on the Indian state of birth does not accurately capture ethnicity, which usually encompasses several other components such as culture, language, and shared norms. In particular, it might be that given India's high cultural fragmentation, the state of birth might capture ethnicity imprecisely. We thus build an alternative measure of ethnicity classifications using the language of employees' native state. Table A.1 shows that, in general, the geographical classification and the linguistic classification are somewhat correlated. When assessing our main results using this alternative classification, we find that the results are in general robust (Table A.6): employees' performance decreased when they faced the loss of a co-ethnic peer who could speak their own language.

Other types of homophily. One might suspect that the ethnic ties we are capturing are confounded with other types of homophily such as gender or age. Table A.7 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.7 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. 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 peculiar 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.[13] Table A.8 shows that the results are robust to controlling for potential confounding effects of time-varying ethnic diversity.

Employee turnover. One might be worried that the decrease in performance that we observed could be caused by employee turnover. It could be that some employees decide to leave their firms once they lose a peer. We thus assess whether the loss of team members is correlated with turnover in any way. Table A.9 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 a co-ethnic colleague due to visa denial. As uncertainty has been found to have a decreasing effect on performance in a variety of settings (e.g., Bloom, 2014), some employees might decide to decrease their exerted effort as a response to a higher perceived risk of future visa denial. Though past research has found that nationality plays an important role in influencing visa approvals (Rissing & Castilla, 2016), this has not been found true for state of birth within countries. Since our sample is composed of all Indian nationals, we believe that this alternative explanation is unlikely to play a role in this setting, given that all employees have the same baseline probability of having their visa denied. If this motivation-related explanation was at play here, we should observe a decrease in performance for both co-ethnic and non-co-ethnic colleagues. As denials increase, all employees, who are all Indian nationals, will experience the same perceived risk of future visa denials.

[13]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.

4.2 Interpreting the Findings

We try to shed light on which underlying mechanism, i.e., 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 extension was 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: teams' 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 a greater drop in performance than teams dealing with more trivial and routine tasks. On the other hand, 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.[14] Specifically, we use bi-gram matching on team-name similarity,[15] and we examine the effect of a loss of a co-ethnic peer separately for teams with low and high task uniqueness (using the median as the reference). The rationale of this measure relies on the fact that teams with relatively common names will most likely perform typical tasks, i.e., routine tasks or tasks that require knowledge and skills that can be easily replaced within the company. For

[14] 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.

[15] Our results are also robust to tri-gram matching (see Table A.11 in the Appendix).

instance, there are roughly 90 teams in our sample that were dedicated to ”infrastructure services delivery”; their names are all slight variations of “ISD US DEL” (e.g., “ISD US DEL NORAM1,” “ISD US DEL NORAM2”). These teams performed similar tasks, which we classify as “typical” for the company. Other teams perform unique tasks, which we classify as “atypical.” For instance, there is only one team in charge of communication with external customers. If this team were to lose a member, her knowledge and skills might not be readily replaced by the organization. Table 5 shows that the negative effect of the loss of co-ethnic peers is stronger if we consider teams with atypical tasks, suggesting it is the loss of knowledge and skills, rather than social incentives, that drive the decline in performance of co-ethnic members.[16]

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 a junior peer 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 a supervisor, then it would be plausible to hypothesize that a decline in performance might be caused by a drop in knowledge transmission, as junior employees may be particularly more reliant on their supervisors' knowledge and skill. We first categorize employees as either junior or senior based on the level of their position.[17] Then we analyze the impact of a loss by classifying departing and remaining team members by position.

Table 6 presents the results from this analysis. Columns 1 and 2 show that the loss of a co-ethnic peer substantially decreased the performance of junior workers, especially when the lost colleague was a co-ethnic supervisor. This is once again evidence that knowledge transfer and learning among team members seem to play much more prominent roles than

[16]One might worry that atypical tasks are just disproportionately assigned to small teams, which would cast some doubts on the role of knowledge in explaining our results. Table A.10 shows that small teams dealing with typical tasks do not experience a drop in performance following the departure of a co-ethnic peer.

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

social incentives in explaining our results. Despite that co-ethnic junior employees might be more likely to form social ties with other junior colleagues, they seem to suffer the departure of a co-ethnic supervisor more. Columns 3 and 4 show that senior employees are not significantly affected by the loss of other team members, regardless of ethnic similarity. This can be explained by the fact that supervisors already possess sufficient knowledge and skills and are not particularly affected by the loss of other knowledgeable supervisors or junior employees. Overall, our evidence points unequivocally at the fact that impaired and weakened knowledge flows, rather than social incentives, drive the decrease in performance of co-ethnic members.

Having clarified which mechanism is responsible for driving our results, we exploit the remaining individual- and team-level information at our disposal to show how the loss of a peer 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 a co-ethnic peer.

We start by examining two team-level features: team size and team diversity. Table 7 shows that the negative effects of the loss of co-ethnic peers are generally driven by workers in small teams.[18] This is also confirmed by Figure A.2 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 a performance decrease after the loss of a co-ethnic peer. Turning to team diversity, Table 8 shows that workers belonging to less ethnically diverse teams experienced a stronger negative shock than workers in more ethnically diverse teams.[19]

Besides leveraging team features, we can also explore possible heterogeneous effects using individual characteristics. When considering age, Table 9 shows how young and old workers

[18] 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 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.

[19] Even in this case, our two mechanisms would work in the same direction: an ethnically homogeneous team might favor social ties, but it might also represent an environment more conducive to knowledge transfer across workers.

are similarly affected by the loss of same-ethnicity peers; however, we notice significant negative effects in particular for male workers (Table 10) and workers with low salaries (Table 11).

Turning our attention to worker quality, Table 12 shows that the loss of a high-quality co-ethnic peer (i.e., a consistently high-performing team member) has a larger negative effect than the loss of a low-quality team member.[20] This result is consistent with a large literature examining the effect of the loss of "star" members on teams (e.g., Azoulay et al., 2010). Interestingly, we also find that workers benefit from the loss of low-performance team members, a result that is in line with the traditional literature on the law of diminishing returns.

5 Discussion

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

We find that small teams, teams working on atypical tasks, and ethnically homogeneous teams are more sensitive to the loss of a peer. When looking at individuals, we find that male workers with a low salary and a low position within the firm suffer the biggest performance drops when a co-ethnic team member leaves, especially if the leaver occupies a relatively high position within the team hierarchy. Our heterogeneity results suggest that the decline

[20]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).

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 contributes to several strands of literature relevant to organizational scholars and economists who study individual productivity. First, it is connected to several studies examining the effects of tighter immigration policies and visa regulations on a variety of economic outcomes at different levels, especially those exploiting changes in the H-1B visa program. Doran et al. (2014) 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 (2010b) find that a reduction in the number of H-1B admissions decreases both immigrant and native patenting activity, while Peri et al. (2015a, 2015b) observe a reduction of tech-related employment and total factor productivity as a result.

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

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

When investigating the role of ethnic ties within organizations, the evidence is more mixed and multifaceted. Lang (1986), for instance, argues that co-ethnic ties within organizations might improve performance because communication is facilitated due to linguistic similarity. On the other hand, Hjort (2014), while examining workers in a flower production plant in Kenya, finds that the presence of co-ethnic ties within firms might spur the emergence of inter-ethnic rivalry and taste-based discrimination among non-co-ethnic peers, negatively affecting the performance of workers. 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. Choudhury and Kim (2019) notice how knowledge recombination is less likely to be pursued by teams composed of co-ethnics. Differently from these studies, we focus specifically on *knowledge workers*, who nowadays represent the largest share of the workforce in every developed country (Drucker, 1999). Our findings also contribute to this literature by highlighting how co-ethnic ties have heterogeneous effects when examining different characteristics of teams and tasks, in line with the work of Marx et al. (2021).

Third, this paper relates to a vast and mixed literature documenting the effects of the loss or influx of peers, and more generally to work corroborating the phenomenon of diminishing marginal returns within teams and sectors. 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) documents that the death of an eminent scientist results in increased performance among noncollaborators in the field but decreased productivity among co-authors. Waldinger (2012) finds no impact on peer performance when investigating the dismissal of high-quality scientists in Nazi Germany. When looking at the loss of scientists who have a propensity to be helpful, Oettl (2012) finds a negative impact on the performance of peers; however, the loss of scientists who do not display prosocial behavior does not influence the output of their peers.

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

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

We believe that our results offer important managerial and policy implications. From a managerial point of view, we emphasize the 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.[21] 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.[22]

By shedding light on which workers are most vulnerable to the loss of peers, our paper

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

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

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.

Finally, our results highlight the importance of team-related dynamics on workers' performance. In particular, we document that as the number of workers in a team increases, marginal productivity diminishes significantly on average, which is consistent with Brooks' observations in *The Mythical Man-Month* (Brooks Jr, 1974). Such evidence should remind managers in knowledge-intensive sectors that teams can be exposed to this seemingly contradictory phenomenon even in contexts where no physical congestion happens. We also highlight an important scope condition of the classic "mythical man-month" argument, i.e., workers bound by co-ethnic ties.

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.[23] By studying the impact of stricter immigration policies on individuals working within heterogeneous teams and departments employing foreign workers, we have highlighted

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

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.

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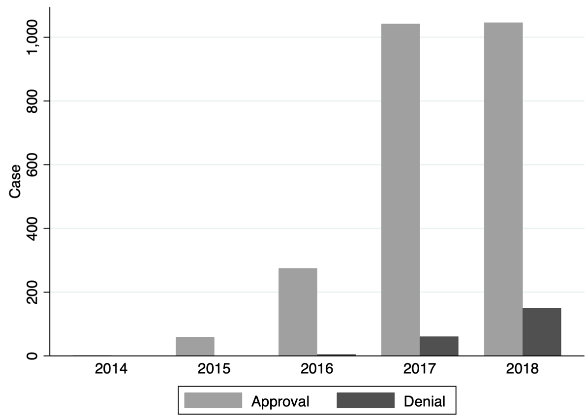
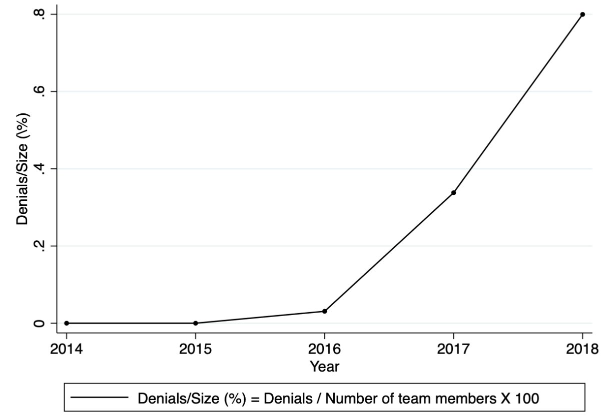
Figures and Tables

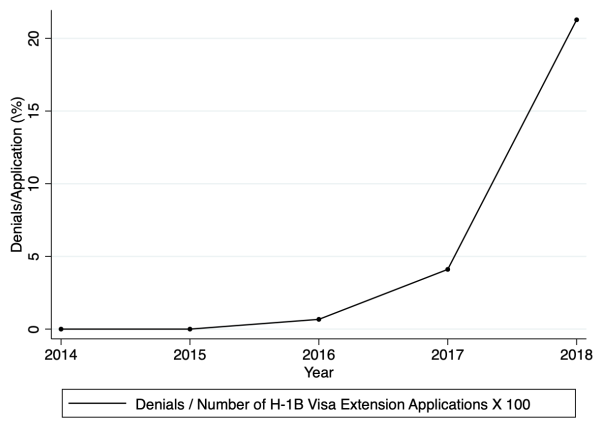
Figure 1: H-1B VISA EXTENSION DENIAL IN OUR SAMPLE



(a) Visa Approvals and Denials



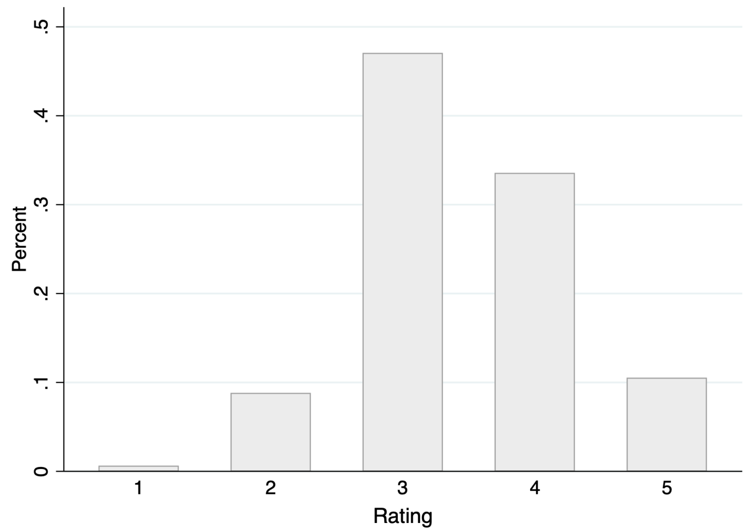
(b) Loss of Team Members



(c) Denial Rate

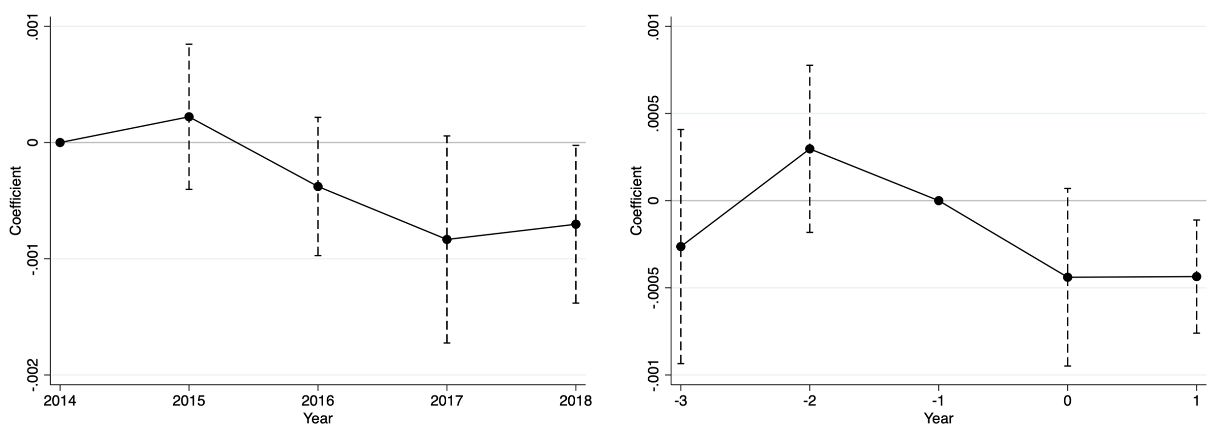
Notes: These figures plot the results of H-1B visa extensions by calendar year in our sample. Plot (a) presents the raw number of H1-B visa extensions approved and denied. Plot (b) shows the percentage of denied cases among the total number of team members (%), and plot (c) shows the percentage of denied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

Figure 2: DISTRIBUTION OF RATINGS AT THE INDIVIDUAL LEVEL



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

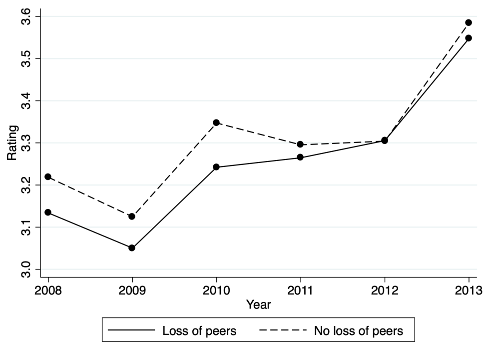
Figure 3: DIFFERENCE-IN-DIFFERENCES IN INDIVIDUAL RATINGS IN RESPONSE TO THE LOSS OF THE SAME-ETHNIC PEERS



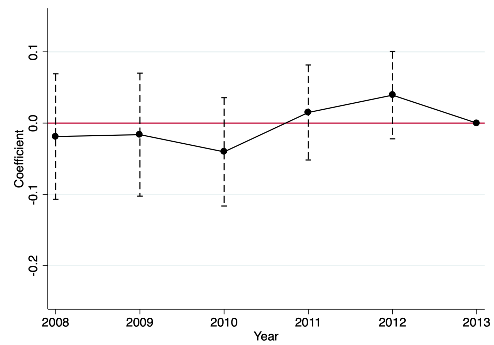
(a) Effect Relative to the Base Year 2014 (b) Effect Relative to a Year Before the Loss

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 use a balanced panel that includes all employee ratings from 2014 and 2018 and we show 95% confidence intervals.

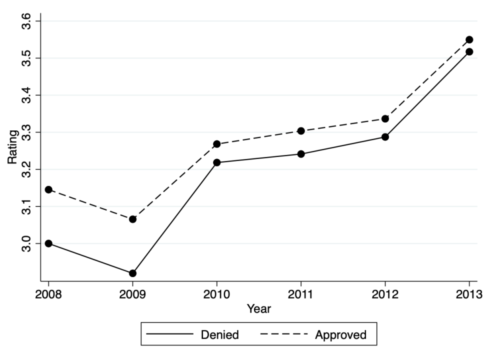
Figure 4: BASELINE INDIVIDUAL RATINGS BY STATUS, 2008–2013



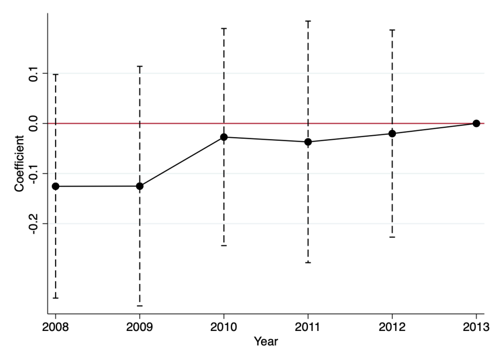
(a) Visa Status of Peers



(b) Visa Status of Peers, Coefficient



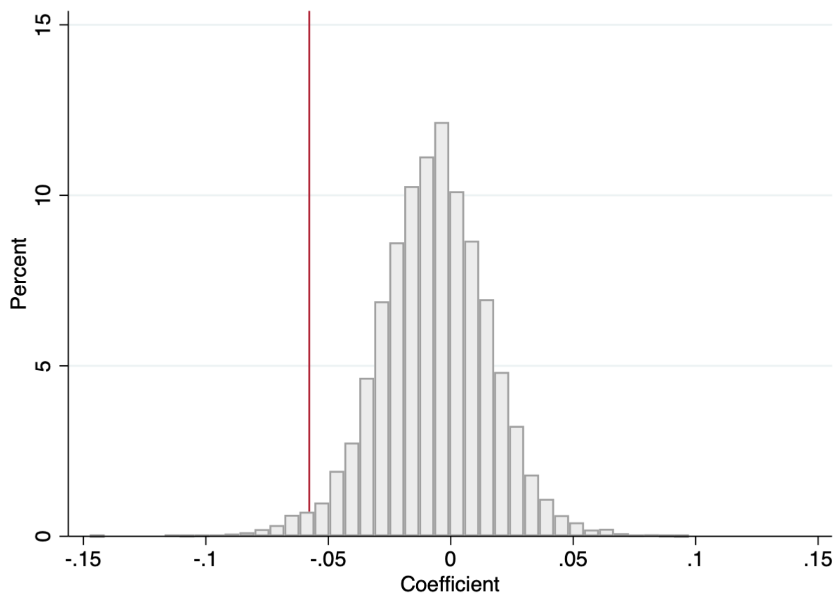
(c) Visa Status



(d) Visa Status, Coefficient

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

Figure 5: PLACEBO TEST



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

Table 1: SUMMARY STATISTICS AT THE INDIVIDUAL, TEAM, AND BUSINESS UNIT LEVEL

	Mean (1)	Median (2)	SD (3)	Min. (4)	Max. (5)
A. Individuals					
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	1981	1981	5	1956	1991
N individuals	6,913				
B. Units					
N project teams	841				
Number of team members	8	2	18	1	245
PeerLoss (= Denials/Size %)	0.160	0	0.647	0	8.333
N business units	187				
Number of team members	37	4	120	1	1,107
PeerLoss (= Denials/Size %)	0.101	0	0.369	0	4.167

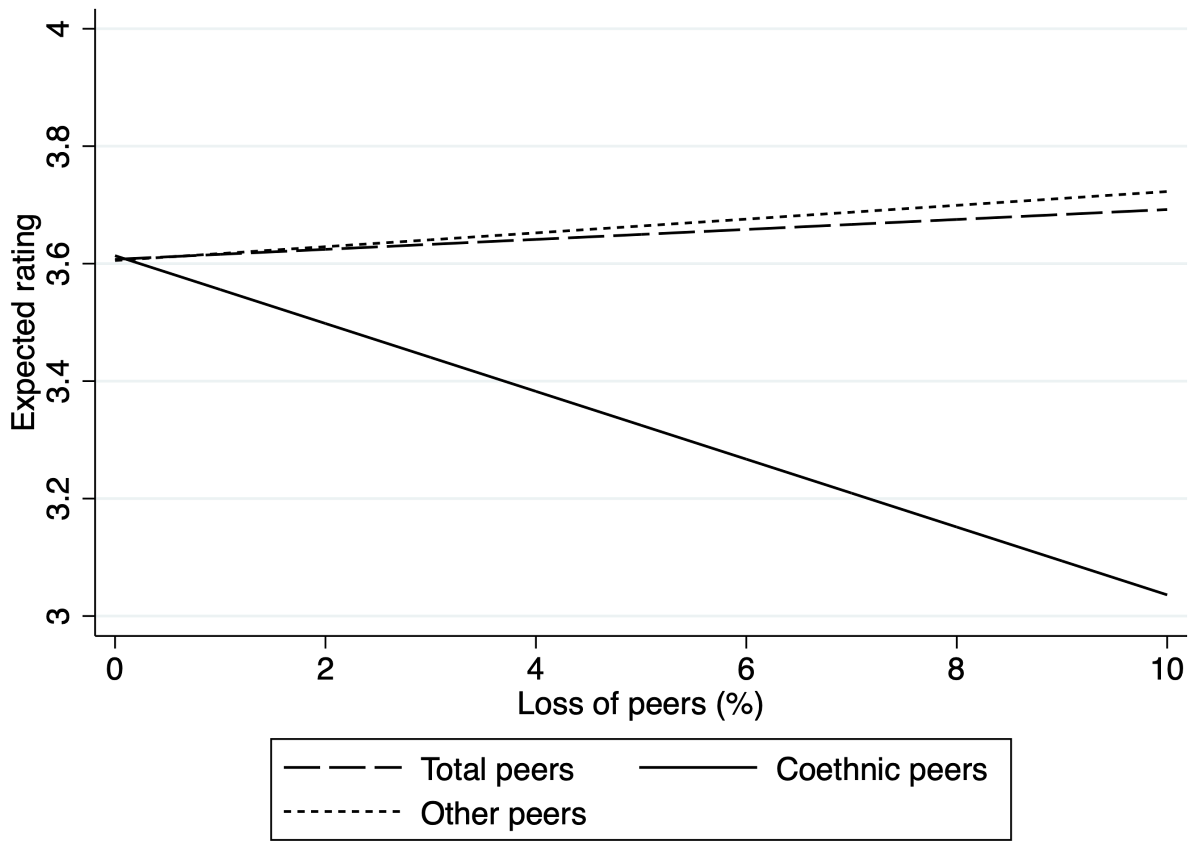
Notes: Observations are at the employee-year level. The average rating is computed as the annual average employee rating between 2008 and 2018. The variable *Rating* presents the proportion of ratings as dummy variables for each rating, which can range from 1 to 5. Panel B shows some basic descriptive statistics of business units and project teams. 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.

Table 2: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS

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

Notes: This table reports the coefficient estimates of the regression in equations 1 and 2 using the sample of employees whose H-1B visa extension was neither denied nor filed. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied. 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 (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Figure 6: 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.

Table 3: BASELINE INDIVIDUAL CHARACTERISTICS BY STATUS

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

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

Table 4: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING, IV ESTIMATES

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

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

Table 5: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING BY TYPE OF TASK

Sample	Atypical Tasks		Typical Tasks	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss	0.004	0.008	0.007	0.012
	(0.005)	(0.006)	(0.006)	(0.007)
PeerLoss	–	-0.072**	–	-0.070
× Same ethnicity		(0.034)		(0.046)
Mean of outcome	3.455	3.455	3.436	3.436
Number of individuals	2,714	2,714	3,368	3,368
Number of units	215	215	215	215
Observations	19,165	19,165	22,732	22,732

Notes: This table reports the coefficient estimates of the regressions shown in equations 1 and 2 using a balanced panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed (for the period 2014-2018). The sample is partitioned into two subsamples based on our measure of task uniqueness (build using a similarity score on teams' names). We use the median value as a threshold to split our sample. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied (*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 6: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING BY POSITION

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

Notes: This table reports the coefficient estimates of the regressions shown in equations 1 and 2 using a balanced panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed (for the 2014–2018 period). The sample is partitioned into two subsamples based on position. We consider entry-level employees and software engineers as juniors, and team leaders and above as seniors. The dependent variable is performance rating per year per person. The treatment variable is the percentage of junior ($LossofJuniors(\%)$) or senior ($LossofSeniors(\%)$) team members whose H-1B visa extension was denied. 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 7: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING BY TEAM SIZE

Sample	Small team		Large team	
	(1)	(2)	(3)	(4)
A. Outcome: Individual ratings of team members				
PeerLoss	0.009*	0.015***	0.006	0.006
	(0.005)	(0.006)	(0.008)	(0.011)
PeerLoss	-	-0.085***	-	-0.020
× Same ethnicity		(0.029)		(0.261)
Mean of outcome	3.534	3.534	3.394	3.394
Number of individuals	1,709	1,709	1,739	1,739
Number of units	378	378	52	52
Observations	15,428	15,428	16,124	16,124
R-squared	0.385	0.385	0.396	0.396
Team members	1-30		31-245	

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. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied ($PeerLoss$). 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 8: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING BY ETHNIC DIVERSITY

Sample	Low initial diversity		High initial diversity	
	(1)	(2)	(3)	(4)
A. Outcome: Individual ratings of team members				
PeerLoss	0.010*	0.016**	0.006	0.010
	(0.005)	(0.006)	(0.007)	(0.008)
PeerLoss	-	-0.075***	-	-0.132
× Same ethnicity		(0.026)		(0.117)
Mean of outcome	3.467	3.467	3.465	3.465
Number of individuals	1,686	1,686	1,762	1,762
Number of units	296	296	134	134
Observations	15,471	15,471	16,081	16,081
R-squared	0.398	0.398	0.389	0.389

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 team ethnic diversity, using the median value of the ethnolinguistic fractionalization (ELF) measure as a threshold. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied ($PeerLoss$). Column 2 shows the results for the loss of the same-ethnicity peers using the regression in equation 2. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

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

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

Notes: This table reports the coefficient estimates of the regressions shown in equations 1 and 2 using a balanced panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed (for the 2014–2018 period). The sample is partitioned into two subsamples based on age. We use the median value as a threshold to split our sample and we define young employees as individuals who would not be more than 33 years old at the start of our period (i.e., 2014). The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied ($PeerLoss$). 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 10: 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 ($PeerLoss$). Column 2 shows the results for the loss of the same-ethnicity peers using the regression in equation 2. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 11: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING BY SALARY

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

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

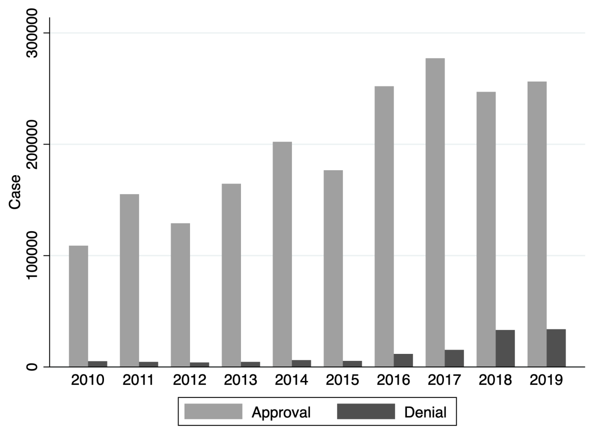
Table 12: EFFECT OF LOSING TEAM MEMBERS AND THE QUALITY OF PEERS

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

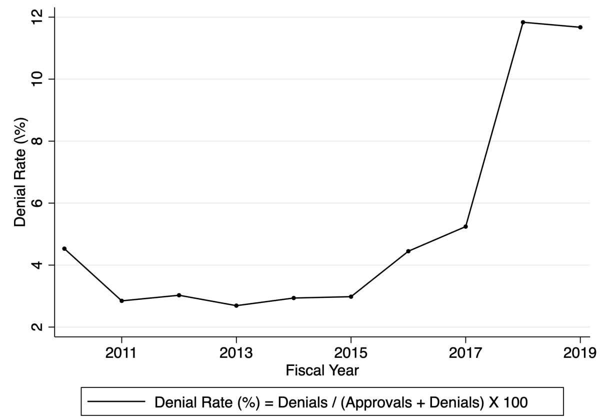
Notes: This table reports the coefficient estimates of the regressions shown in equations 1 and 2 using a balanced panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed (for the 2014–2018 period). A high-performance peer is defined as a team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

Appendix Figures and Tables

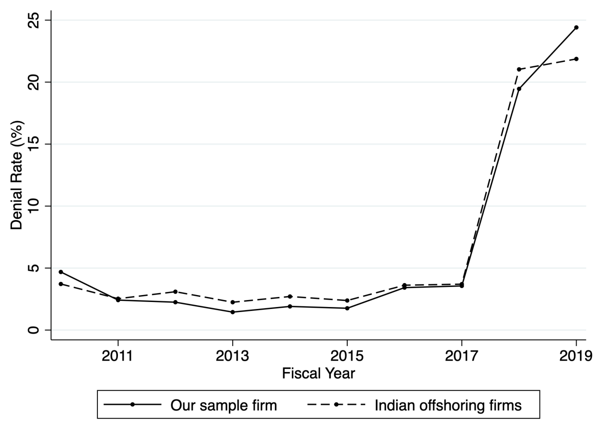
Figure A.1: H-1B VISA EXTENSION APPROVALS AND DENIALS FROM ADMINISTRATIVE DATA (FISCAL YEARS)



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



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

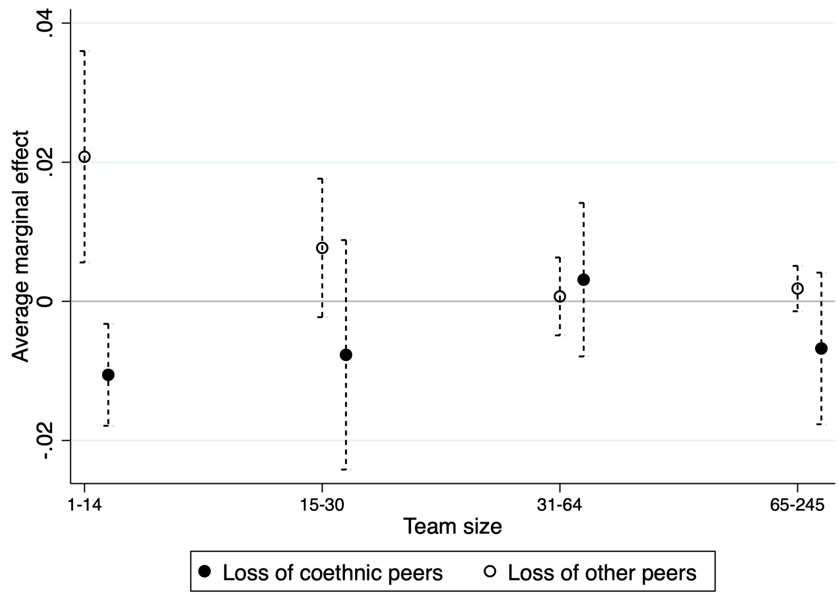


(c) Visa-Extension Denial Rate (sample firm vs. Indian offshoring firms)

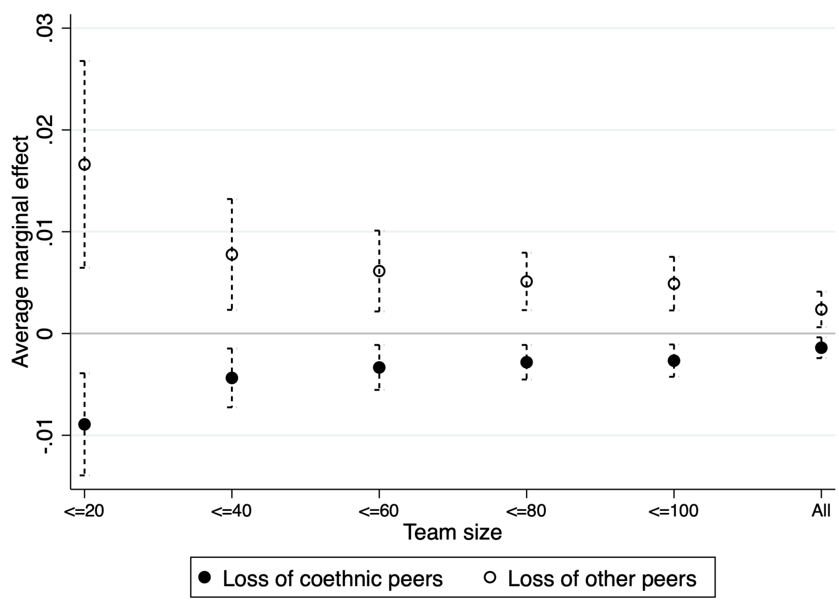
Notes: Figures (a) and (b) presents data about all petitions filed with USCIS requesting an extension of existing H-1B visas (primarily for existing employees at the same company) from the USCIS H-1B Employer Data Hub. These data include all the visas extensions filed in the United States, for all employers.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

Figure A.2: AVERAGE MARGINAL EFFECT BY TEAM SIZE

(a) Team size (four subgroups)

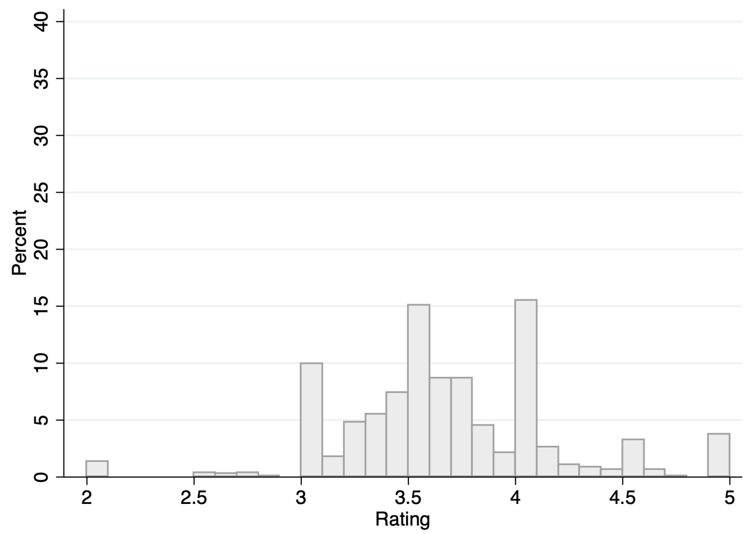


(b) Maximum team size



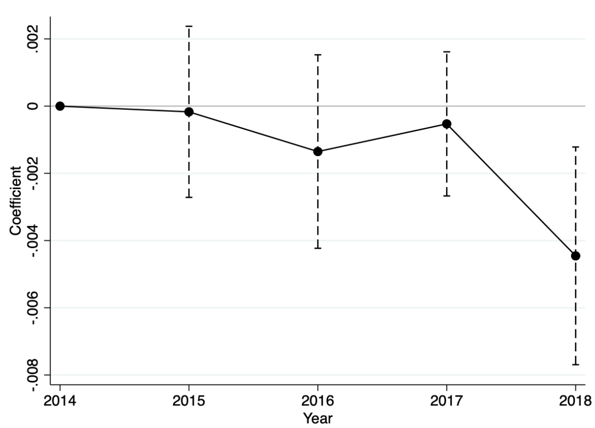
Notes: The figures shows the average marginal effect by team size and maximum team size (i.e., the average marginal effects on increasingly bigger groups). The average marginal effects present the coefficient estimates of the regression considering the average loss of peers with 95% confidence intervals.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

Figure A.3: FREQUENCY DISTRIBUTION OF RATING AT THE TEAM LEVEL

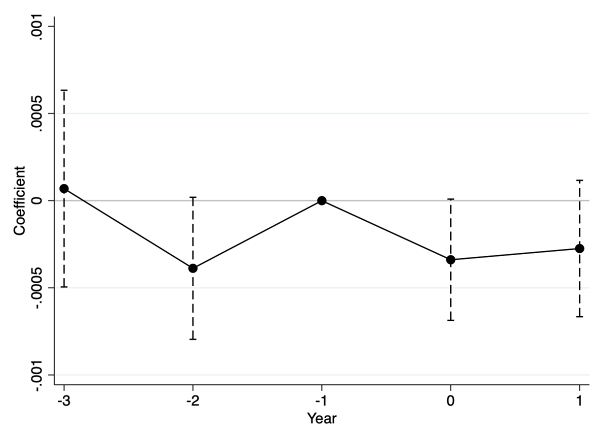


Notes: This histogram presents the percentages of the frequency of average team ratings.

Figure A.4: DIFFERENCE-IN-DIFFERENCES IN INDIVIDUAL RATINGS IN RESPONSE TO THE LOSS OF THE SAME-ETHNICITY PEERS (BUSINESS UNIT)



(a) Effect Relative to the Base Year 2014



(b) Effect Relative to a Year Before the Loss

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

Table A.1: ETHNIC CLASSIFICATION

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

Table A.2: SUMMARY STATISTICS AT THE PROJECT-TEAM LEVEL

	Mean (1)	Median (2)	SD (3)	Min. (4)	Max. (5)
A. All teams (2016–2018)					
Team rating	3.672	3.638	0.501	2	5
H-1B visa extensions filed	2.681	1	5.323	0	64
H-1B visa extensions denied	0.134	0	0.512	0	6
Team members (size)	18.910	9	27.773	1	253
PeerLoss	0.551	0	2.714	0	50.0
Number of teams	334				
Observations	1,002				
B. Teams that lost team members					
Team rating	3.639	3.606	0.274	3	5
H-1B visa extensions filed	6.567	3	8.940	0	64
H-1B visa extensions denied	0.558	0	0.927	0	6
Team members (size)	42.750	30	44.053	2	253
PeerLoss	2.300	0	5.177	0	50.0
Number of teams	80				
Observations	240				
C. Teams that did not lose any team members					
Team rating	3.682	3.667	0.554	2	5
H-1B visa extensions filed	1.457	1	2.430	0	20
H-1B visa extensions denied	0	0	0	0	0
Team members (size)	11.402	7	13.017	1	77
Number of teams	254				
Observations	762				

Notes: Observations are at the team-year level. We use raw data about team ratings provided directly by the company (i.e., we do not aggregate using individual team members' ratings in this case). Column 1 presents the annual average of each variable between 2016 and 2018 at the team level. The average number of H-1B visa extensions filed by employee per team/year and the average number of denied cases are shown.

Table A.3: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATINGS: ALTERNATIVE OUTCOME VARIABLES AND AGGREGATION LEVELS

Sample (Year)	Balanced (2014–2018)		Unbalanced (2008–2018)	
	(1)	(2)	(3)	(4)
A. Outcome: Team rating				
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
B. 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 dependent variable in panel A is team rating (raw data at team level provided by the company); in panel B, it's individual ratings aggregated at the business-unit level. The treatment variable is the percentage of team members whose H-1B visa extension was denied (*PeerLoss*) at the project-team level in panel A and at the business-unit level in panel B, respectively. Columns 1 and 2 show the results for a balanced panel that has all employee ratings from 2014 and 2018 while columns 3 and 4 use an unbalanced panel from 2008 and 2018 that contains some missing values for our outcome variable in some years. Columns 2 and 4 show the results for the loss of the same-ethnicity peers using the regression in equation 2. Standard errors are clustered at the team level in panel A and at the business-unit level in panel B. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A.4: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING, ORDERED LOGIT ESTIMATES

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

Notes: This table reports the ordered logit estimates using the sample of employees whose H-1B visa extension was neither denied nor filed. The dependent variable is performance rating per year per person, in an ordered index that ranges from 1 to 5. The treatment variable is the percentage of team members whose H-1B visa extension was denied ($PeerLoss$) 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.5: PLACEBO TEST: EFFECT OF LOSING TEAM MEMBERS AND OTHER ETHNICITY ON INDIVIDUAL RATINGS

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

Notes: This table reports the coefficient estimates of the regression for a placebo test that exploits the loss of the other-ethnicity peers. We consider the sample of employees whose H-1B visa extension was neither denied nor filed. Columns 2 and 4 show the results for the loss of the other-ethnicity peers using the regression in equation 2. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied ($PeerLoss$) 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.6: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING (LINGUISTIC CLASSIFICATION)

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

Notes: This table reports the coefficient estimates of the regression in equations 1 and 2 using the sample of employees whose H-1B visa extension was neither denied nor filed. In this robustness check, we use a linguistic classification instead of state of birth to identify employees of the same ethnic groups. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied ($PeerLoss$) 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.7: EFFECT OF LOSING TEAM MEMBERS ON INDIVIDUAL RATING BY THE TYPE OF TEAM MEMBER

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

Notes: This table reports the coefficient estimates of the regression in equation 2 using a balanced panel that includes all employees whose H-1B visa extension was neither denied nor filed in the 2014–2018 period. The dependent variable is performance rating per year per person. $PeerLoss$, our treatment variable, is defined as the percentage of team members whose H-1B visa extension was denied at the team level. 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.8: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING WITH ADDITIONAL CONTROLS

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

Notes: This table reports the coefficient estimates of the regression in equations 1 and 2 using the sample of employees whose H-1B visa extension was neither denied nor filed. We include additional variables in the regression that control for potential confounding effects of ethnic diversity. Specifically, we include two time-varying controls: the proportion of same-ethnicity peers in the team, and the ethnolinguistic fractionalization (ELF) measure, which is computed as one minus the Herfindahl index of ethnic group shares. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied ($PeerLoss$) at the team level. 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.9: 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 ($PeerLoss$). 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.10: THE EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING BY THE TYPE OF TASKS AND TEAM SIZE

Type of tasks	Atypical tasks		Typical tasks	
Team size	Small (1)	Large (2)	Small (3)	Large (4)
Outcome: Individual ratings of team members				
PeerLoss	0.013*	-0.020	0.020**	0.022*
	(0.007)	(0.014)	(0.008)	(0.012)
PeerLoss	-0.099***	0.439	-0.068	-0.225
× Same ethnicity	(0.037)	(0.440)	(0.051)	(0.315)
Mean of outcome	3.504	3.403	3.538	3.413
Number of teams	188	27	184	31
Observations	7,677	9,880	9,461	11,360

Notes: This table reports the coefficient estimates of the regression shown in equation 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 four subsamples based on task type and team size. The dependent variable is performance rating per year per person. The treatment variable is the percentage of junior ($LossofJuniors(\%)$) or senior ($LossofSeniors(\%)$) team members whose H-1B visa extension was denied. Standard errors are clustered at the team level. The interaction coefficients between small and large teams for both typical and atypical tasks are statistically different from each other. Standard errors are clustered at the team level (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A.11: EFFECT OF LOSING TEAM MEMBERS AND ETHNICITY ON INDIVIDUAL RATING BY TYPE OF TASK (TRI-GRAM MATCHING)

Sample	Atypical tasks		Typical tasks	
	(1)	(2)	(3)	(4)
Outcome: Individual ratings of team members				
PeerLoss	0.000	0.005	0.011**	0.014**
	(0.005)	(0.007)	(0.005)	(0.006)
PeerLoss	-	-0.064*	-	-0.061
× Same ethnicity		(0.037)		(0.038)
Mean of outcome	3.434	3.434	3.454	3.454
Number of individuals	2,842	2,842	3,240	3,240
Number of units	215	215	215	215
Observations	19,230	19,230	22,667	22,667
R-squared	0.424	0.424	0.432	0.432

Notes: This table reports the coefficient estimates of the regressions shown in equations 1 and 2 using a balanced panel that includes all the performance ratings of employees whose H-1B visa extension was neither denied nor filed (for the period 2014-2018). The sample is partitioned into two subsamples based on our measure of task uniqueness (build using a similarity score on teams' names). We matched team's name using a tri-gram matching algorithm. We use the median value as a threshold to split our sample. The dependent variable is performance rating per year per person. The treatment variable is the percentage of team members whose H-1B visa extension was denied ($PeerLoss$). 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 (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).