Undervaluing Skilled Immigrants

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Abstract

Firms employing more H-1B visa holders realize abnormally high stock returns, particularly on earnings announcement dates. Excess returns are higher in talent clusters: doubling the number of H-1B workers in a city doubles the effect of a firm's own H-1B hiring on its future returns. The surprise election of President Trump in 2016 had an immediate, negative effect on firms benefiting from the H-1B visa program. The results suggest that the stock market was slow to recognize value creation associated with skilled immigrant labor.

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"In technology, it's about the people." – Marissa Mayer, former CEO, Yahoo!

"I'd rather interview 50 people and not hire anyone than hire the wrong person." – Jeff Bezos, Founder and former CEO, Amazon

"Hire right, because the penalties of hiring wrong are huge." – Ray Dalio, Author and Investor

"The secret to my success is that we've gone to exceptional lengths to hire the best people in the world." – Steve Jobs, Co-Founder and former CEO, Apple

1 Introduction

Quotes like these are both typical and ubiquitous in the financial press, suggesting a nearly universal perception among top executives that a firm's workforce is a critical factor in the creation of shareholder value. Although intuitive, the argument implicitly relies on frictions that prevent highly skilled workers from being paid enough to fully capture their marginal product. Such friction may relate to monopsony power that allows firms to extract rents that might arise from synergies between employees, moving and search costs, coordination frictions, or perhaps regulation. The broad family of advantages that firms derive from such considerations falls under the umbrella of *organization capital* (Prescott and Visscher, 1980).

Viewed through this lens, it is clear how the H-1B foreign worker program might create a fruitful environment for value creation.[1] On the productivity side, visas are awarded based on unique, specialized skills, often in science and technological fields where information spillovers may be especially important. At the same time, the extent to which H-1B workers capture the associated surplus is unclear. Holders of H-1B visas are typically linked to sponsoring firms, and changing jobs is difficult. This is reinforced by (as we show) strong geographical clustering of

[1] The H-1B visa program, established in 1990, allows U.S. employers to temporarily hire foreign workers in specialty occupations that require highly specialized knowledge, often in fields like technology, engineering, and science. For much of its early history, the program was sparsely used; throughout the 1990s and early 2000s, annual applications seldom reached the annual quota and drew little attention from the public or financial media. This changed around 2006, when demand for H-1B visas began to regularly exceed supply and a lottery system was implemented.

H-1B employers, effectively limiting job search to a handful of U.S. cities.

In this paper, we document the superior stock price performance of the public firms hiring the most H-1B workers. Especially noteworthy is that these positive excess returns persist for *well over a decade*. This suggests three possible explanations: First, H-1B visa usage may proxy for a priced risk factor. Second, H-1B usage may proxy for an omitted variable, like growth opportunities, that may be independently related to future returns. Finally, H-1B workers may have created substantially more value than the market initially anticipated, leading to return predictability over long horizons.

Our first set of results quantifies the excess returns of firms that employ the most H-1B workers. When sorted by H-1B visa applications, the top quintile outperforms the other four groups by about 20 basis points per month. We find very little difference between the returns of the other quintiles. Returning to the possible explanations for these findings, standard risk adjustments make almost no difference, with alphas being nearly identical to the differences in raw returns between high and low H-1B sorted portfolios. Cross-sectional regressions that control for a variety of firm fundamentals and benchmark returns against industry averages (using Fama-French 49 industry classifications) continue to show strong and significant excess returns for firms hiring more H-1B workers. These excess returns are not driven solely by the high-tech industry (as returns are already adjusted for industry averages) nor by a few large technology firms employing the highest numbers of H-1B workers. For example, the excess returns remain robust even after removing FAANG stocks, excluding the largest firms above the NYSE 90th size percentile, or excluding the top 10% of firms with the most H-1B employment.

While conventional approaches to benchmarking risk fail to explain much of the effect, two pieces of evidence suggest that the excess returns were associated with higher than expected cash flows. First, several measures of firm fundamentals can be predicted from lagged H-1B hiring, in particular growth in sales, earnings, and R&D. Second, returns around earnings announcements display an especially strong effect. High H-1B firms have consistently high cumulative abnormal returns (*CARs*) during weeks with either actual or anticipated earnings announcements, accounting for most of the estimated yearly alpha, suggesting that the abnormal return is associated with unexpected earnings.

Though not dispositive, the above results are consistent with a persistently sluggish market reaction to the cash flow implications of H-1B hiring. A remaining question, however, is whether the market was slow to recognize the value created by H-1B workers specifically, or rather to unobserved heterogeneity correlated with H-1B hiring. The remainder of the paper addresses this question, but because labor decisions are endogenous to current and expected firm fundamentals, our conclusions are not definitive.

The most sharply identified test is an event study around the election of Donald Trump in 2016. Several factors make this a useful laboratory for addressing omitted variables possibly correlated with H-1B hiring. First, the election outcome was a surprise, with then-candidate Trump being a 2-to-1 underdog, thereby affording the test statistical power. Second, Trump explicitly made immigration a focal point of his candidacy, with members of his advisory team having explicitly considered pausing or ending various visa programs, including the H-1B program. At the same time, we are not aware of any other firm, industrial, or locational attribute that received similar opprobrium from the campaign.

To wit, the overall stock market reacted *positively* to Trump's victory, with the S&P 500 and NASDAQ increasing 1.5% and 1%, respectively, over the five-day window surrounding the election. At the same time, firms hiring the most H-1B workers experienced a near-immediate value *decline* of roughly 1%, relative to their industry-matched peers. Note that this finding of negative short-run returns is not inconsistent with positive long-run alphas over the full sample. To the contrary, the long-horizon evidence merely suggests that the stock market consistently under-estimated the value of the H-1B program, not that it believed it to be worthless. The election event study is well identified under the relatively weak assumption that, whatever the market's estimation of shareholder value created by the H-1B program, Trump's election was interpreted as bad news.

The remaining tests provide suggestive evidence that the stock market reacted gradually to value created by H-1B workers. Our workhorse for this part of the paper is geographical variation. H-1B visas are disproportionately awarded to firms in a few key cities, among them the San Francisco Bay Area, Seattle, and New York City. Following Peri, Shih, and Sparber (2015), we proceed under the assumption that there exist observable characteristics of these cities that make them particularly attractive to foreign-born workers. While we cannot directly observe all relevant factors, the identifying assumption is that these city-level characteristics are not systematically correlated with omitted firm or industry fundamentals.

One characteristic is whether a city is home to an "Immigrant Integration Office," which provides a range of support services for foreign-born residents.[2] Another characteristic is the percentage of a city's residents that identify as Asian (including South Asian), based on the observation that about 85% of H-1B applications are from China and India. While these city-level attributes may be strongly correlated with H-1B hiring, they tend to be relatively stable over time, making them unlikely to reflect ebbs and flows of resident firms' prospects.

We then use these city-level variables alongside firm-level characteristics as explanatory variables in a first-stage regression predicting H-1B hiring. Both sets of variables provide strong explanatory power. In a second stage, we run a horse race between city- and firm-level fitted values as forecasting variables for future stock returns. The city-level information strongly explains future returns, but the firm-level information does not. While a non-causal interpretation for this finding is possible, it seems unlikely that attributes of a firm's urban environment (e.g., the racial makeup of its headquarter city) would capture future prospects better than its own fundamentals. A causal interpretation, on the other hand, simply takes our existing hypothesis one step further: if the stock market was slow to understand the impact H-1B workers had on firm

[2]Some of the key functions include helping welcome immigrants and encourage receptivity, stressing the economic contributions of immigrants to the regional economy, developing, streamlining and consolidating services for immigrants to promote inclusive policies, etc.

values overall, it is perhaps unsurprising that regional variation in H-1B workers was similarly misunderstood.

The paper concludes with an empirical analysis of potential information spillovers between local firms, mediated by H-1B workers. For example, foreign workers may work more productively in communities with a higher concentration of similar workers, or alternatively, may be attracted to such locations in the first place. In either case, we hypothesize that the productivity of a firm's own H-1B workers is amplified by a high concentration of H-1B workers in the local environment. To explore this idea, we estimate a regression of stock returns as a function of firm-level H-1B hiring intensity, the aggregate H-1B hiring intensity in the firm's headquarter city, and an interaction term between the two. The estimated interaction is highly significant: the return premium a firm experiences roughly doubles with each standard deviation in city-level H-1B hiring. In a refrain to our original motivation, the inability of workers to capture productivity spillovers in wages should be reflected in the firm's performance, which appears to be the case.

Our paper contributes to a nascent literature on high-skilled immigrant labor, particularly H-1B visa holders, and their role in shaping economic outcomes. Prior research has examined how H-1B hiring affects innovation and labor productivity. Some studies find that more H-1B workers lead to higher rates of innovation and improved labor productivity (Kerr and Lincoln, 2010; Ghosh, Mayda, and Ortega, 2014), while others argue that hiring more H-1B workers crowds out local workers and has modest impacts on firm patenting activity (Doran, Gelber, and Isen, 2022; Wu, 2018).[3] More recent studies find that access to high-skilled foreign labor is crucial for the success of start-up companies and hedge funds (Chen, Hshieh, and Zhang, 2021; Dimmock, Huang, and Weisbenner, 2022; Chen, Hshieh, Teo, and Zhang, 2024). Conversely, restrictions on hiring skilled foreign workers reduce investment (Xu, 2025a,b), increase offshoring by U.S. multinationals (Glennon, 2024), and drive "acqui-hiring" through mergers and acquisitions (Chen, Hshieh, and Zhang, 2024). While this body of work primarily focuses on how skilled immigrant labor influences innovation and broader corporate decisions, our study extends

[3] See Kerr (2013) for a review of this literature.

the literature by examining the contribution of H-1B workers to shareholder value and evaluating the potential causal link between access to foreign talent and firm value creation.

We also contribute to a separate but related literature on the role of labor force dynamics in asset pricing and corporate behavior. Several studies show that labor mobility and hiring adjustment costs negatively affect firm value (Belo, Lin, and Bazdresch, 2014; Belo, Li, Lin, and Zhao, 2017; Shen, 2021). Zhang (2019) finds that firms with routine-task labor hedge against macroeconomic shocks through labor-technology replacement, lowering expected returns. Chen, Zhang, and Zhang (2022) show that talent retention risk limits corporate investment. Eisfeldt and Papanikolaou (2013) focus on the risk of losing key talent and document a strong link between stock returns and proxies for organization capital.[4] While these studies predominantly examine labor effects through the lens of discount rates and risk premia, our analysis emphasizes the impact on expected cash flows and the market's ability to recognize and price these effects in a timely manner.

In this respect, our work is closely related to Agrawal, Hacamo, and Hu (2021), which uses LinkedIn data to measure firm-level flows of rank-and-file employees and shows that such flows predict near-term movements in both stock returns and fundamentals. In their paper, the authors interpret ebbs and flows of workers at time t as signals about innovations in firms' future general prospects. Our research provides a complementary channel through which a particular type of high-skilled workers—H-1B visa holders—contributes to firm values.

Another related strand of literature examines the link between firm headquarters location and firm value. For example, Dougal, Parsons, and Titman (2022) find that after controlling for industry, firms in "glamour" locations tend to have higher market-to-book ratios and experience higher expected rates of return, particularly in the 1990s. We provide complementary evidence linking these glamour locations to firms' ability to attract foreign talent, showing that access to this talent has generated excess returns in recent periods.

[4]For more on organization capital, see Prescott and Visscher (1980), Lev and Radhakrishnan (2005), Peters and Taylor (2017), and Eisfeldt, Kim, and Papanikolaou (2022).

2 Data

2.1 H-1B Applications

Our empirical analysis focuses primarily on applications for H-1B worker visas. We use the Disclosure Data from U.S. Department of Labor during 2008 to 2020 fiscal years. The data are generated by the Office of Foreign Labor Certification (OFLC), a division of the Employment and Training Administration within the Department of Labor. The OFLC provides annual releases of disclosure data on Labor Condition Application (H-1B, H-1B1, E-3), PERM, H-2A, H-2B, etc. The data are organized by the federal fiscal year (October 1 through September 30). For our study, we focus on the disclosure data for Labor Condition Application, the first step toward obtaining an H-1B visa.

Initiated annually by firms, Labor Condition Applications (LCA) are batched in a first-come-first-served basis starting in April, for employment (usually) beginning in October. The administrative data for LCAs is maintained and published in a disclosure file (Form ETA-9035),[5] and is updated annually to reflect the reporting period (April-October) over which LCA applications may be approved. For example, the release for the fiscal year 2022 refers to LCAs filed between March 31, 2021 and October 1, 2021.

The typical LCA contains several fields describing attributes of the application including the timing (e.g., date received, decision date), applicant (e.g., firm, address), legal details (e.g., lawyer, name of state and highest court), job (e.g., title, occupational code), and a unique case identifier. Also indicated is the term of employment, usually three years, which can be renewed once for a total of six years.

Most LCA petitions refer to a position expected to be filled by a single worker. However, there are occasional exceptions, whereby firms aggregate multiple positions with the same job titles and categories within the same LCA. The relevant field here is “TOTAL_WORKER_POSITIONS,” a

[5] https://flag.dol.gov/sites/default/files/2019-09/ETA_Form_9035.pdf

field added in 2018. Because these data are not available for prior years (i.e., 2017 and before), it is not possible to weight LCA applications by the number of workers prior to 2018. However, diagnostic analysis suggests that this data limitation is empirically trivial.

To assess this, for each year 2018, 2019 and 2020, when TOTAL_WORKER_POSITIONS is a listed field, we calculate two firm-level H-1B usage measures using either: (1) the raw number of LCAs, or (2) the sum of TOTAL_WORKER_POSITIONS requested in all LCAs, both scaled by the firm's total labor force in the prior year. From 2018 to 2020, the correlation (in the cross-section of firms) between these measures is 0.96 (see Internet Appendix Table A.1). The correlation using ranks, which is the basis for most of our analysis, could be even higher. This exercise suggests that the informational loss when using the raw number of LCAs, as in Xu (2025a,b), Ghosh, Mayda, and Ortega (2014), and Chen, Hshieh, and Zhang (2021), scaled by the firm's existing (lagged) number of workers, is very small and overwhelmed by the benefit of extending the dataset backward more than a decade.

Another set of fields describe different reasons why a firm might apply for an LCA. These include applications for new workers (often after graduating from domestic universities), renewals for existing H-1B workers, amendments to existing applications based on changes in the job description, change of employer, etc. As with the fields described above, these data became available starting in 2018, which prevents us from analyzing them separately for most of our sample period. Fortunately, the effect seems limited mostly to scaling. Similar to the above, for each of the years 2018-2020, we calculate firm-level H-1B usage measures using the raw number of LCAs (our main measure) and, alternatively, the number of workers being requested for certification for: (1) new employment, (2) continued employment, (3) non-amended positions, and (4) change of employer, all scaled by the firm's total labor force in the prior year. The pairwise correlations between our main measure and each of these alternative measures remain fairly high, ranging from 0.83 to 0.96 across all years (see Internet Appendix Table A.1).

Practically, what this means is that although the mix of reasons for why firms apply for LCA varies, their *relative ratios* appears stable both in the cross-section of firms and over time. In other words, if roughly half of LCAs pertain to new employees on average, this fraction does not vary much between firms, nor does it change much year to year. Hence, yearly rankings are not particularly sensitive to which measure of LCAs we use, giving us confidence that the raw number of LCAs (which we use for our analysis) accurately reflects the underlying variation. In the rest of the paper, we use "H-1B petitions" or "H-1B applications" to replace the more formal term "LCAs."

We take three steps to link H-1B employers in the DOL Disclosure Data to firms in CRSP and COMPUSTAT databases. First, we separately match H-1B employer names with CRSP company names and COMPUSTAT historical company names, respectively. We start with machine matching and then for pairs with reasonable matching scores, we manually correct matching errors. Second, we identify big H-1B employers as those that have filed more than 900 petitions over 2008 to 2020 fiscal years (about 350 employers). We manually check the matching results to ensure that these big H-1B employers are properly matched with CRSP and COMPUSTAT firms (if they are public firms). Lastly, we combine the matched pairs of employers-CRSP firms and employers-COMPUSTAT firms. If an employer is matched with a CRSP firm but not with a COMPUSTAT firm, or vice versa, we use the successful match. In some rare cases, an employer is matched with different firms in CRSP and COMPUSTAT, and in this case we follow the employer-CRSP match.

For about 77% of the petition records in the original DOL Disclosure Data, we cannot match the employers with CRSP or COMPUSTAT firms. Most of these petitions are filed by private firms, universities, research institutions, nonprofit organizations, etc. Our analysis focuses on the remaining 23% of the petition records, for which we have successfully matched the employers with firms in CRSP or COMPUSTAT. For each firm or employer, we sum up the total petitions filed in a fiscal year.[6] This gives us 25,566 firm-year observations.

A once-public employer may have filed petitions before it goes public or after it is delisted.

[6]We use all petitions regardless of the case status (certified, withdrawn, or denied). Our main results are quantitatively similar if we use only certified petitions.

Though the employer is matched to a firm in CRSP or COMPUSTAT, it is not covered by these databases during the pre-IPO or post-delisting years. We address this issue by dropping fiscal years before an employer goes public and after it is delisted. This leaves us 15,383 firm-year observations as our final sample, covering 3,025 unique CRSP firms.

2.2 Geography

We use several data sources for the analysis on geography and demographics. To examine the geographic distribution of H-1B petitions, we obtain firms' historical headquarter location data from COMPUSTAT. We map the zip codes of firm headquarters to core-based statistical areas (CBSAs), which refer collectively to metropolitan and micropolitan statistical areas, using the ZIP-CBSA crosswalk mapping file provided by U.S. Department of Housing and Urban Development (HUD).[7] To evaluate the degree of racial diversity of headquarter cities, we use the county-level population data by race from the U.S. Census's American Community Survey (ACS).[8] We use the ACS 2010 5-year estimates, which cover the data collected from January 2006 to December 2010.

2.3 Other Variables

Lastly, we extract data from CRSP and COMPUSTAT for financial variables such as stock returns, market capitalization, total employees, book-to-market ratios, investment, profitability, sales, net income, R&D expenses, etc. Our analysis also controls for accounting-based estimates of organization capital employed by prior studies. Our final sample includes all NYSE, AMEX, and NASDAQ common stocks with CRSP share codes of 10 or 11.

[7] https://www.huduser.gov/portal/datasets/usps_crosswalk.html

[8] https://www.census.gov/programs-surveys/acs

3 Summary Patterns of H-1B Petitions

3.1 Secular and Geographic Variation

Temporal. We begin by documenting some broad aggregate patterns in H-1B petitions. The blue line in Panel A of Figure 1 plots the time-series of all H-1B applications for our sample of public firms from 2008 through 2020. Total applications increased during the eight years of the Obama presidency (2009-2016), before leveling off during the Trump administration (2017-2020). In the same figure, the grey line plots the fraction of public firms with non-zero H-1B applications, hovering around 30% with little variation. Given that the number of public firms has been steadily decreasing for decades (including the horizon plotted), Figure 1 thus indicates a strong increase on the intensive margin: although roughly the same number of firms (1,000-1,300) apply for H-1B workers annually, on average, each firm applies for triple the number of positions.

There are at least two factors responsible for this secular trend. The first is that firms' demand for skilled foreign-born workers has increased. A second is due to the nature of the H-1B visa approval process itself. In 2004 (prior to the start of our sample), a cap of 65,000 visas (plus 20,000 additional visas granted for applicants with graduate degrees) was imposed for private sector positions.[9] Because firms during these years could not expect approval for all submitted petitions, there may have been an incentive to apply for more workers than available positions. While relevant for the time-series, note that neither factor plays an important role in our analysis, which is primarily cross-sectional, i.e., comparing firms with high and low applications for H-1B workers, at a given point in time.

Sectoral. Panel B of the same figure shows the variation in applications across sectors. Overwhelmingly, the demand for H-1B workers is from science and technology-related fields (about 87% of positions), which we aggregate by combining the following subcategories:

[9]For a brief period from 1998-2004, the American Competitiveness and Workforce Improvement Act of 1998 and American Competitiveness in the Twenty-First Century Act of 2000 temporarily increased the allotment to 195,000 visas, but the cap reverted to 65,000 visas in 2004. See Glennon (2024) for a detailed characterization of how and why H-1B caps have evolved through time.

computer and mathematical, architecture and engineering, and life, physical, and social science occupations. Together, finance and management positions account for about 10% of positions.

Geographical. To quantify the extent to which H-1B visa applications are more or less concentrated in specific areas, we aggregate the total number of H-1B petitions in each CBSA over 2008 to 2020 fiscal years, across all firms headquartered in the CBSA. Figure 2 shows the geographic distribution, which indicates significant clustering, particularly on the east and west coasts. The top four CBSAs with a total of over 50,000 petitions are New York-Newark-Jersey City (NY/NJ), San Jose-Sunnyvale-Santa Clara (CA), Seattle-Tacoma-Bellevue (WA), and San Francisco-Oakland-Berkeley (CA). The next two CBSAs, with over 20,000 petitions each, are Boston-Cambridge-Newton (MA/NH) and San Diego-Chula Vista-Carlsbad (CA). The top five cities account for two-thirds of the total H-1B applications and the top ten cities account for almost 80%.

3.2 H-1B Applications Across Firms

Our empirical tests primarily focus on the ability of firm-level variation in H-1B usage to forecast stock returns. The main variable of interest is $H1BIntensity_{i,t}$, defined as the logarithm of the number of H-1B applications made by firm i in year t ($H1B_{i,t}$) scaled by lagged (year $t-1$) total employment (COMPUSTAT item EMP).[10] Table 1 reports summary statistics for H-1B usage, as well as various auxiliary control variables, as defined in Appendix A. The unit of observation is the firm-year pair. Panel A characterizes the sample of firm-years involving at least one H-1B application (roughly one quarter of the data), whereas Panel B presents summary statistics for all other firm-years (i.e., those making no H-1B applications). Means and variances reflect winsorization at the 1% threshold, within each fiscal year.

The first row of Panel A (the raw number of H-1B applications) indicates a highly right

[10]Specifically, $H1BIntensity_{\text{i,t}} = ln(H1B_{\text{i,t}}) - ln(EMP_{\text{i,t-1}} + 1)$. Because the distribution of total employment (in thousands) is highly right skewed and more than a quarter of the sample firms have $EMP_{\text{i,t-1}} < 1$, we add a constant value of one to $EMP_{\text{i,t-1}}$ before applying the log transformation.

skewed distribution, with a median of 5 applications, but on average almost an order of magnitude larger (47 applications). Most of this reflects the underlying right skewness in the distribution of firm size itself, note the skewness for both *EMP* (number of employees) and *MarketCap* (market capitalization), given that larger firms will naturally have higher demand for all workers. Accordingly, when we size-adjust H-1B applications in row 2, much of the skewness is removed, but nonetheless reveals considerable cross-firm heterogeneity. Across all applications, on a per-employee basis (row 2), firms in the 75^{th} percentile apply for H-1B visas eight times ($\frac{e^{1.48}}{e^{-0.65}} \approx 8.4$) as often as those at the 25^{th} percentile.

Part of the H-1B application includes a field for the anticipated salary of the applicant. The third row reveals that in general, H-1B workers tend to be well paid, with an average (median) salary of $\$94,539$ ($\$91,817$), and with relatively modest variation (standard deviation of $26,082). Adjusting these figures for inflation results in similar variation (in relation to the mean): in 2020 dollars, the mean H-1B salary is $\$104,030$, with a standard deviation of $\$27,034$.

The remainder of Panel A and, by nature of the relevant sample, all of Panel B pertain to control variables (see definitions in Appendix A). Most of these are standard, such as market capitalization, book-to-market ratio, and various growth-based measures of performance. Comparing Panels A and B reveals that firms making H-1B applications tend, on average, to be larger, have lower book-to-market ratios, and grow faster in terms of sales and research-and-development. Moreover, firms that utilize H-1B workers are associated with higher values of organization capital (*OrgCap*), as defined in Eisfeldt and Papanikolaou (2013).

Table 2 stratifies firms into quintiles based on their H-1B intensity. Starting with row 1, firms with zero H-1B applications tend to be the smallest, both in terms of market capitalization ($3 billion) and number of employees (6,600). Progressing down the table reveals that demand for H-1B workers exhibits a strong, negative relation with the number of employees. Firms in the lowest quintile of applications are almost four times as large (31,000 workers) as those in the top quintile (8,500), with the middle three groups in between. However, a similar comparison of market capitalization suggests a more nuanced, U-shaped relation. Firms in the top quintile of H-1B applications are the largest on average ($13 billion market capitalization), with the next largest size quintile being those with the fewest applications ($10 billion). Book-to-market ratios convey a similar message: firms in the top quintile have the lowest average B/M of any group (0.32), indicating a strong relation between growth opportunities and demand for skilled foreign-born workers.

Despite such a clear "glamour-value" distinction in terms of overall H-1B applications, the wage differential is comparatively muted. Firms in the smallest H-1B quintile (i.e., firms with large employee bases but relatively low H-1B worker ratios) pay foreign-born workers about $91,000 average, with modest increases in each progressive group ($95,000 in quintile 4). The highest wages are offered by the top quintile, at around $100,000 annually.

Given that our main analysis compares average stock returns across H-1B groups, as a preliminary step toward addressing possible risk differences, the last column contains summary statistics on market betas, estimated from a market model with monthly returns, $R_P - R_f = \beta \times (MKT{-}R_f)$. Although firms in the highest quintile have the highest market betas of any group (1.07), the relation is not monotonic (the lowest is quintile three at 0.86), and in any case, the differences in the betas of the portfolios are small.

4 Skilled Foreign Labor and Firm Performance

This section presents estimates of the relation between the tendency of firms to hire H-1B visa holders and their future stock returns. Recall that we are testing a joint hypothesis. The first part of the hypothesis is that the stockholders of firms with a comparative advantage in either attracting or utilizing this form of skilled labor capture part of the associated surplus. The second part of the hypothesis is that the value created by highly skilled workers is not fully appreciated, so market prices may have initially underreacted to this source of value. Because some of the excess returns we measure can potentially represent risk premia, we calculate excess returns in a variety of ways that account for different sources of factor risk as well as different characteristics that are associated with excess returns.

4.1 Stock Returns

4.1.1 H-1B sorted portfolios

We begin by sorting firms into portfolios based on their H-1B intensities, and examine portfolio returns from one to five years after the ranking dates. At the end of each fiscal year *t*, firms are ranked into five portfolios (Low, 2, 3, 4, and High) based on *H1BIntensity*, and firms with no H-1B petitions are included in a sixth portfolio (Zero). The portfolios are value-weighted and rebalanced at the end of fiscal year $t + 1$. For each portfolio, we form industry-matched portfolios and calculate the monthly returns of the H-1B portfolios net of the returns of the corresponding industry portfolio. For this benchmarking, we calculate value-weighted industry portfolio returns each month, using the Fama-French 49-industry categories.

Panel A of Table 3 reports these industry-adjusted returns for various horizons after formation (e.g., one year after the ranking date, two years, etc.). As the table shows, the annual excess return of the high H-1B portfolio is over 2% in the first year after formation relative to the matched industry portfolio, with a t-statistic exceeding four. The returns of all of the other H-1B sorted portfolios are close to zero. Notably, the returns at each horizon are similar, which reflects that H-1B hiring patterns are relatively persistent, and as a result, portfolios formed based on last year's H-1B intensity are similar to those based on H-1B intensities several years earlier.

The non-linear pattern seen in Panel A may shed light on the underlying mechanism. Under monopsony alone, whereby firms are simply hiring skilled labor at a discount, we would expect a roughly linear relationship, since hiring 100 H-1B workers at a 20% discount should create about twice as much value as hiring 50. On the other hand, if skilled workers generate complementarities with other employees, value creation may be non-linear. As the number of skilled workers increases, the number of potential interactions among them grows exponentially, which can amplify productivity gains. If firms capture most of the value from these complementarities via organization capital, a non-linear relationship between H-1B employment and firm performance would be expected.

Panel B of Table 3 reports annualized (industry-adjusted) returns and alphas of the six portfolios benchmarked against standard factor models. We calculate industry-adjusted monthly returns and regress them on the CAPM, the Fama-French 5-factor model (Fama and French, 2015), the 6-factor model that adds a momentum factor (Fama and French, 2018), an augmented q-factor model that incorporates an expected growth factor known to capture much of innovation-related excess returns (Hou, Mo, Xue, and Zhang, 2021), and a behavioral model designed to capture long- and short-horizon mispricing effects (Daniel, Hirshleifer, and Sun, 2020). As shown in the table, after controlling for these prominent risk- and mispricing-based factors, the resulting alphas remain strong and statistically significant, ranging from approximately 2% to 3% per year, with t-statistics between two and three.

Further robustness checks reported in Internet Appendix Table A.2 show that when we exclude the largest firms with market capitalization above the 90^{th} percentile of NYSE size breakpoints, the results remain robust, with yearly alphas exceeding 3%. Thus, the finding is unlikely to be solely driven by the exceptional growth of large technology firms in recent years.

4.1.2 Fama-MacBeth regressions

We next estimate Fama-MacBeth cross-sectional return regressions that include firms' H-1B intensity (*H1BIntensity*) in fiscal year $t - n$, where n varies from 1 to 5, along with controls for other firm characteristics. Note that *H1BIntensity* is defined in the firm-year sample with at least one H-1B petition, and it is set to zero for the firm-year observations with no H-1B petition. To capture average returns of zero-H1B firms, we add an indicator, *ZeroH1B*, that equals one if a firm has no H-1B petition in fiscal year *t – n*, and zero otherwise.

To account for other firm characteristics that may be associated with stock returns, the regressions control for market capitalization (*logMarketCap*), book-to-market ratio (*logBM*), asset growth (*AG*), and operating profitability (*OperProfit*) in fiscal year *t – n* (the same fiscal year as H-1B petitions), as well as market beta (*Beta*), momentum (*Ret (t-12, t-2)*) and reversals (*Ret (t-36, t-13)*) at the previous month end. Importantly, we control for the organization capital (*OrgCap*) measure employed in Lev and Radhakrishnan (2005) and Eisfeldt and Papanikolaou (2013).[11] Lastly, we include the Fama-French 49-industry fixed effects. The results reported in Table 4 are very similar to that in Table 3. The coefficients of *H1BIntensity* are positive and statistically significant in all five columns, suggesting that firms' H-1B intensities predict stock returns in the following five years. In contrast, most of the other potential determinants of returns are not reliably significant.

Table 5 shows the results of various robustness checks. Our results hold when using the Fama-French 17 industry classifications instead of Fama-French 49, and when excluding firms located in New York or California (Columns 1–2). To address the concern that our results may be driven by a small number of firms with the highest H-1B employment, we remove FAANG stocks (Facebook/Meta, Apple, Amazon, Netflix, and Alphabet/Google), exclude the top 10% of firms with the highest H-1B hiring, or exclude the largest firms with market capitalization above the 90^{th} percentile of NYSE size breakpoints (Columns 3–5); in all cases, our findings remain robust. To examine whether variations in the denominator of the *H1BIntensity* measure (i.e., total employees) influence our results, we include annual changes in total employees as a predictor (Column 9); in another regression, we separately include H-1B hiring and total employees in the same model (Column 10). The results suggest that the value creation effect is attributed specifically to H-1B workers rather than to variations in total employees. Additionally, the H-1B applications data from the U.S. Department of Labor does not include disclosure dates. To

[11] For each firm i in year t, $OrgCap_{it} = (1-\delta)OrgCap_{it-1} + SG\&A_{it}/CPI_t$, where SG&A refers to selling, general, and administrative expenses, *CPI* is the consumer price index during year t, and δ is the annual depreciation rate. See also the variable definition in Appendix A.

mitigate potential look-ahead bias and ensure that H-1B hiring information is publicly available to investors, we introduce a three-month gap after the fiscal year-end (end of September) before measuring stock returns (Column 6), and our results remain robust to this adjustment.

Another potential concern is that the excess returns of high H-1B portfolios may be correlated with, or subsumed by, innovation-related portfolios, as H-1B workers contribute to firm value through innovation. Goyal and Wahal (2024) show that a cash-based operating profitability factor fully captures the excess returns of innovation-related portfolios sorted by the R&D expenditures or economic value of patents. To determine the extent to which the H-1B effect is driven by innovation, we include additional control for R&D capital of Chan, Lakonishok, and Sougiannis (2001) (Column 7), or replace operating profitability with the cash-based operating profitability measure of Ball, Gerakos, Linnainmaa, and Nikolaev (2016) (Column 8). While these additional controls slightly weaken our results, they remain robust, suggesting that H-1B workers contribute to firm value creation not only through innovation but also via other mechanisms, such as enhancing operational efficiency. Their contribution extends beyond the typical innovation premium.

4.1.3 Calendar time results

Figure 3 plots the cumulative excess returns of firms with high or low H-1B applications. Panel A displays the comparison between one dollar invested in the "High" H-1B portfolio (corresponding to the top quintile from Table 3) and the "Zero" H-1B portfolio. Over the roughly twelve years from late 2008 through the end of 2020, the differential performance steadily widens, especially accelerating after 2015. By December 2020, the nominal value of a dollar invested in the high H-1B portfolio had grown to over $10, about three times the value of the zero H-1B portfolio.

While this pattern may appear obvious in hindsight, H-1B visas were lightly used and largely overlooked by the general or financial media since the program's founding (through the

Immigration Act of 1990) through the mid-2000s. During this same period, however, the nature of production was rapidly changing, with ideas and intangible assets replacing physical goods as key drivers of value. As a result, the market may have underreacted not only to the role of the H-1B program itself, but also to the growing complementarity between highly skilled labor and advancing technologies, which helps explain the sharp acceleration in value creation from H-1B workers after the mid-2010s.

Panel B shows this comparison on an industry-adjusted basis. The blue dashed line, corresponding to the industry-adjusted returns of the Zero H-1B portfolio, hovers around one over the entire sample, indicating no abnormal performance in either direction. The red solid line, however, displays similar excess returns as in Panel A, though with lower absolute magnitude. The aggregate difference is about 40 percentage points ($1.4 versus $1.0) which, over the 147 months shown, suggests a return premium of about 0.23 percent per month, similar to the comparison shown in Table 3. Lastly, we observe a calendar-time pattern—though less pronounced than in Panel A using raw returns—in which higher excess returns for high H-1B portfolios are concentrated in the second half of the sample.

4.1.4 Industry effects

Given that firm-level portfolio sorts on H-1B hiring generates differences in average returns, we explore the analogous question at the industry level, i.e., whether sorting industries by their H-1B usage explains the cross-section of average industry returns.

One reason why this is plausible is because the program is large, with an estimated 500,000–700,000 workers currently under H-1B visas.[12] However, this underestimates the cumulative impact since its inception in 1991, since many H-1B visa holders will go on to receive permanent work visas (green cards). Indeed, in the San Francisco Bay Area, the 2025 Silicon

[12] According to USCIS population estimates, the H-1B authorized-to-work population was approximately 583,420 as of September 30, 2019 (USCIS, 2019). Unfortunately, USCIS provides this estimate only for 2019 rather than as a recurring annual report. Based on the 2019 figure and subsequent net growth in approvals, we estimate the current number of active H-1B visa holders is likely in the 500,000–700,000 range.

Valley Index estimates that two-thirds of Bay Area tech workers are foreign-born,[13] and the vast majority of them are either current or former holders of H-1B visas.[14] An industry-level analysis therefore tells us whether H-1B hiring can explain the cross-section of industry returns, as we have already seen in the cross-section of stock returns (within industries).

Interestingly, this turns out *not* to be the case. We begin by splitting the sample annually into three industry groups, based on H-1B intensity aggregated to the industry level (using FF-49 designations). In Panel A of Table 6, the first column reports the average raw return (row 1) for the lowest industry-H1B tercile, followed by alphas with respect to various factor models. Shown in the adjacent columns are results for the middle and highest terciles. The main takeaway is a null result: although the point estimates generally favor high-H1B industries, the high-minus-low difference is never statistically significant.

Another relevant perspective is the share of STEM (science, technology, engineering, and mathematics) workers within an industry, given that the majority of H-1B workers are employed in STEM occupations. While we do not have firm-level data on STEM degrees or other technological credentials, we can conduct an industry-level analysis. The National Science Foundation reports data on STEM occupations across NAICS industries.[15] We manually match NAICS codes to the Fama-French 49 industries and then sort industries into terciles based on STEM prevalence, measured as the percentage of workers in each industry employed in STEM occupations (using 2021, the most recent data).

Panel B of Table 6 presents the average industry portfolio returns and alphas relative to standard

[13] `https://jointventure.org/download-the-2025-index`

[14] The most typical path proceeds from studying in the United States on an F-1 student visa, transitioning to employment through Optional Practical Training (OPT), and subsequently obtaining an H-1B work visa.

[15] See: National Science Board, National Science Foundation. 2024. The STEM Labor Force: Scientists, Engineers, and Technical Workers. *Science and Engineering Indicators 2024*. NSB-2024-5. Available at https://ncses.nsf.gov/pubs/nsb20245/. Table SLBR-20 provides the prevalence of STEM workers in select industries by occupation group, based on 2021 data sourced from the Census Bureau's American Community Survey, 1-year public-use file. Industries were selected if the percentage of S&E (science and engineering), S&E-related, or STEM-middle skill workers in that industry was at least 2.5 times the percentage of all U.S. workers in the indicated STEM group. Based on this criterion, six of the 49 Fama-French industries were not selected and therefore excluded from our analysis: Entertainment (Fun), Wholesale (Whlsl), Restaurants, Hotels, and Motels (Meals), Banking (Banks), Insurance (Insur), and Trading (Fin).

factor models. Consistent with the corresponding industry-level analysis based on H-1B usage, we find no statistically significant excess returns for high-STEM industries over our sample period. Once again, this indicates that the important source of variation arises primarily across firms within industries, rather than across industries themselves.

On the other hand, double sorts on firm-level H-1B employment and industry-level STEM prevalence, reported in Panel C of Table 6, produce intuitive patterns. Among low- and medium-STEM industries, the spread in excess returns between high- and low-H1B firms is small and statistically insignificant. However, among high-STEM industries, the spread is 53 basis points per month and is statistically significant at the 1% level. It suggests that the marginal effect of H-1B employment is most pronounced in STEM-intensive industries, where the demand for highly skilled labor is greatest.

While these empirical patterns would appear to support the idea that value created by H-1B workers is distinct from that created by tech/STEM workers generally, we do not regard these tests as dispositive. STEM is a broad category that includes many technical fields (such as aerospace and healthcare) where H-1B workers are not commonly employed. Hence, even the double-sort analysis above cannot rule out the possibility that non-H1B STEM workers in subfields that frequently hire H-1B employees are driving the observed excess returns. In other words, in areas with H-1B hiring, unobserved heterogeneity in either technology or non-H1B human capital could confound a causal interpretation, a possibility we acknowledge.

4.2 Fundamentals

As with any analysis of difference in excess returns, the patterns in the prior section can arise either from risk differences or unexpected cash flow news. The fact that high H-1B firms had slightly higher market betas and somewhat lower book-to-market ratios suggest that there can be relevant risk differences; however, we expect that these differences are small and captured by our various risk proxies. To gain a more direct sense of whether firms, stratified by H-1B applications, have different future operating performance, we run various regressions on fundamentals. Specifically, we run annual panel regressions of sales growth, earnings growth, and R&D expenses growth on lagged H-1B hiring intensity, motivated by the idea that efficiency gains generated by H-1B workers—whether operational or technological—will eventually be reflected in these outcome measures. Sales growth (*SalesGrowth*) is measured as the logarithm of sales in year t minus the logarithm of sales in year t–1. Earnings growth (*EarningsGrowth*) is defined as the change in net income from year t–1 to year t divided by total asset in year t–1. R&D expenses growth (*R&DGrowth*) is calculated as the logarithm of R&D expenses in year t minus the logarithm of R&D expenses in year t–1. We add industry$\times$year fixed effects and cluster standard errors by firm.

Table 7 reports the results. In Panel A, the positive coefficients of *H1BIntensity* suggest that firms hiring more H-1B workers have higher sales growth ($p < 1\%$) over the next 5 years. In terms of magnitudes, a one-standard-deviation increase of *H1BIntensity* is associated with higher sales growth of 17.5% to 27.5% relative to the mean (0.08, in Panel A of Table 1). Likewise, Panel B shows that firms hiring more H-1B workers have higher earnings growth ($p < 5\%$) around 3 years ahead. Here, a one-standard-deviation increase in *H1BIntensity* would increase earnings growth substantially by 225% relative to the mean (0.004, in Panel A of Table 1). Panel C conveys a similar message, showing that firms hiring more H-1B workers have higher growth in R&D expenses ($p < 1\%$) over the ensuing five years. A one-standard-deviation increase of *H1BIntensity* is associated with an increase in the growth of R&D expenses of 60% to 82% relative to the mean (0.05, in Panel A of Table 1). Note that in all three cases, increases in H-1B hiring are associated with durable increases in fundamentals, with the results lasting several years after the application date.

4.3 Returns Around Earnings Announcements

In this subsection, we estimate the extent to which H-1B intensity predicts returns around earnings announcement dates. Since the timing of earnings announcements is (roughly) known in advance, but the news content is not, the predictability of reactions around these dates provides a good test of our hypothesis that the market initially underreacts to the information embedded in H-1B intensity. These tests are based on the assumption that a firm's systematic risk is not unusually high in the days surrounding earnings announcements.

To define the earnings announcement period, we follow two approaches commonly used in the literature. The first approach uses the actual earnings release date, obtained from the COMPUSTAT quarterly database (RDQ). Because earnings announcements on a specific day—rather than being delayed—are generally interpreted as good news, returns on these dates tend to exhibit a slight positive bias on average. To correct for this, the second approach uses an "anticipated" announcement date, following prior studies such as Savor and Wilson (2016). For actual announcement dates, we compute cumulative abnormal returns (*CAR*) in excess of the market factor over the [-2, 1] window around the announcement. For anticipated dates, we calculate the *CAR* over the same week as the anticipated announcement.

We run quarterly Fama-MacBeth regressions of firms' abnormal returns around quarterly earnings announcements on past H-1B intensity. The *CAR* for each quarter is calculated as the cumulative abnormal return around each announcement (either [-2, 1] or over the same week) and then summed across all earnings releases in that quarter. Cross-sectional regressions of firm-level *CAR* are estimated at the quarterly level, and coefficients are averaged over time. The key variable of interest is *H1BIntensity* in fiscal year $t-n$, where n varies from 1 to 5. Control variables are the same as in Table 4, estimated either in fiscal year $t-n$ or at the previous quarter end .

Table 8 reports the results. For both actual and anticipated announcement dates, high H-1B firms experience positive excess returns around quarterly earnings releases. The magnitudes and statistical significance are strongest when using actual earnings dates (Panel A); a one-standard-deviation increase in H-1B intensity is associated with an excess return around earnings announcements of about 10 basis points, depending on the horizon. Using anticipated earnings dates (Panel B), the effect is about half as large, with sensitivities in the range of 5 to 7 basis points, statistically significant in all but the first year.

When interpreting these results, we note two observations. First, the effect exhibits both strengthening and durability, growing from year 1 to year 2 and from year 2 to year 3, and tailing off only slightly five years after the sort date. This pattern dovetails with the hump-shaped pattern observed for two of the three fundamental measures in Table 7 (sales and earnings growth). The consilience in timing paints a consistent picture: H-1B workers contribute to firm value with a multi-year lag, which the stock market initially fails to fully recognize. However, over time, improvements in fundamental performance (much of which represent positive surprises) lift the stock price, generating the higher average returns experienced by investors of high H-1B firms.

Second, the coefficients between the *short-horizon* return regressions in Table 8 and the *monthly* Fama-MacBeth estimates in Table 4 are broadly similar. For example, the average H-1B coefficient between Panels A and B in Table 8 are 0.086 for year 2, 0.085 for year 3, and 0.07 for year 4, greater than the corresponding coefficients of 0.075, 0.067, and 0.048 in Table 4. However, the earnings response coefficients in Table 8 are measured over horizons four to five times shorter than that in Table 4, meaning that the return sensitivity to H-1B hiring is at least four to five times larger around earnings releases. Another way to appreciate the differential magnitudes is to replace the continuous measure of *H1BIntensity* in Table 8 with an indicator for a firm being in the top H-1B quintile. As reported in Internet Appendix Table A.3, the coefficient on this dummy variable, *High_H1BIntensity*, is around 0.5, depending on the horizon and whether we use actual or anticipated earnings dates. This suggests that of the approximately 2% average excess returns experienced by the highest H-1B quintile (relative to the other quintiles) in Table 3, a majority portion (0.5% times four quarters) is realized during the few days surrounding quarterly earnings releases.

4.4 Dynamic Effects

Recall the calendar-time pattern observed in Figure 3, where the higher excess returns earned by high H-1B portfolios are concentrated in the second half of the sample. A natural question is whether a similar pattern appears in firms' fundamentals, as reflected in operating performance or earnings announcement returns. To investigate this, we split the sample into two subperiods: an early period covering fiscal years 2008–2013 and a late period covering fiscal years 2014–2020. We then compare improvements in firms' fundamental performance following the hiring of H-1B workers between the early and late halves of our sample.

First, we examine the three fundamental measures considered earlier in the paper—sales growth, earnings growth, and R&D growth—across the two subperiods. The results, reported in Panel A of Table 9, show that the magnitudes for sales growth and R&D growth are similar in the early and late halves of the sample. On the other hand, earnings growth is neither significant in the full sample (as shown in Table 7) nor in either subperiod. This may partly reflect the fact that operating performance measures such as sales and earnings growth are notoriously volatile, often exhibiting large percentage swings from year to year. For this reason, we prefer to study the effect around quarterly earnings announcements and focus on stock returns, whose statistical properties are better understood.

Panel B of Table 9 examines earnings announcement returns across the two subperiods: early (2008–2013) and late (2014–2020). Here, we obtain cleaner and sharper results than those based on operating measures. Using actual announcement dates (left panel), we find a weaker effect in the early period and a stronger effect in the late period. Using anticipated announcement dates (right panel), the effect appears only in the later period. These findings suggest that fundamental improvements, as reflected in earnings surprises, are modest in the early years and become more concentrated in later years, which may help explain the calendar-time pattern observed in Figure 3.

5 Presidential Election of 2016

To this point, we have shown that the hiring of skilled foreign-born workers is associated with superior operating performance over the ensuing years and that these improvements are reflected in stock prices with a multi-year lag. While the high returns associated with the hiring of skilled labor may indicate value created by a firm's ability to attract talent, our results may also reflect the possibility that firms simply hire more talent when their prospects, as embodied by their non-human sources of value, improve. In this section, we use the 2016 U.S. presidential election as a natural experiment to investigate the potential causal impact of hiring skilled foreign labor on firm value.

Recall that immigration was a centerpiece of the Trump campaign. Although most frequently targeting illegal, land-based immigration (particularly through the southern border of United States), Trump's platform was widely regarded, and was represented, as being anti-immigration. For example, early in his campaign, Trump's website called for eliminating H-1B visas, arguing that foreign workers are holding down American salaries and hurting employment rates, although he later softened his stance on this particular program.[16]

The 2016 election provides a good experiment because the outcome was considered a surprise. At the national level, the final polls had Trump trailing Clinton by 3 to 4 percentage points. More critically, Clinton's polling advantage in swing states such as Wisconsin, Michigan, and Pennsylvania—collectively known as the "Blue Wall" which had uniformly been won by Democratic nominees since the 1980s—were considered by the Clinton campaign to be relatively safe.[17] Betting and prediction markets in the days immediately preceding the election identified Trump as a heavy underdog, with odds indicating a win probability of roughly 25%.[18] Hence, by virtually all measures, Trump's eventual victory represented a significant surprise to financial

[16] See: *CNBC* (October 28, 2015), "Trump: Only in favor of legal immigration", and *The Economic Times* (March 5, 2016), "Donald Trump's flip-flop over H1B visa lands him in controversy".

[17] See Polls from RealClear Politics: "2016 Ohio: Trump vs. Clinton".

[18] See: *CNBC* (November 7, 2016), "Betting sites see record wagering on US presidential election".

markets.

The combination of Trump's stance on immigration and pre-election odds offers a promising setting for evaluating the extent to which the H-1B program may have contributed to the values of the hiring firms. In particular, we expect that firms most exposed to the H-1B program would be especially vulnerable, and hence, should be associated with the largest value declines. To test this idea, we compare the returns of the portfolios of the highest and lowest quintiles of firms, ranked by their H-1B intensities, in the days around the November 2016 election. Since we will be reporting returns during the 3- and 5-day windows around the election, we bootstrap standard errors by measuring the mean and standard deviation of the 3- and 5-day returns of these same portfolios over the preceding 180 days. Panel A of Table 10 indicates an average 3-day (5-day) return of 0.02 (0.04) percent for the highest H-1B quintile, with a sample standard deviation of 0.19 (0.25) percent. Comparable estimates for the lowest quintile of H-1B firms are 0.00 (0.00) percent of average returns with a sample standard deviation of 0.20 (0.24) percent. All of these return patterns are calculated net of each firm's Fama-French 49-industry average.

We are interested in whether stock returns of high H-1B firms were especially poor in the days around the November 8, 2016 election, relative to the portfolio-level volatility observed in the preceding 180 days. Over the three-day window immediately after the election, the cumulative return of the highest H-1B quintile (net of industry averages) is -0.46 percent, deviating from the sample mean (0.02) by 0.48 percent, more than twice as large as the sample standard deviation of 0.19 percent. The five-day return patterns are similar: the cumulative industry-adjusted return for the highest H-1B portfolio is -0.73 percent, more than three times the sample standard deviation (0.25) away from the sample mean (0.04).

By comparison, neither the lowest quintile of H-1B firms (but excluding firms with zero H-1B workers) nor the Zero H-1B portfolio exhibits a strongly significant abnormal response to Trump's surprise victory. The differential return between the highest and Zero H-1B quintiles over the three-day window is -0.54 percent, deviating from the sample mean by 0.57 percent, more than twice as large as the sample standard deviation of 0.26 percent. The return patterns are similar, or even stronger, over the five-day window. Panel A of Figure 4 displays the returns of these H-1B portfolios around the November 8, 2016 election, showing a sharp decline the day after the election for the highest H-1B portfolio only, which continues to trend downward for five days thereafter.

It is worth reiterating that the low- and high-H-1B comparisons are net of industry effects, since all returns are benchmarked against their industry averages. A remaining concern is that the observed return patterns may reflect city- or state-level factors—such as political leanings, exposure to policy uncertainty regarding international trade, or tax policy changes under the Trump administration—rather than firm-level exposure to the H-1B program. While using the tighter industry controls based on the Fama-French 49 industry categories should control for a large part of these policy uncertainties affecting certain industries, we further address potential location-based confounds by adjusting returns for firms in key Democratic-leaning states such as New York and California.

Recognizing the potential overlap between locations and industries (e.g., most tech firms are located in California), we implement the following procedure for firms in these two states. First, we regress the value-weighted average returns of all New York-based firms (and separately, all California-based firms) on value-weighted average returns of the Fama-French 49 industries. We then subtract the residuals from these regressions—which capture location-specific returns orthogonal to industry performance—from the industry-adjusted returns of firms in each respective state. As shown in Panel B of Table 10 and displayed graphically in Panel B of Figure 4, this additional adjustment actually strengthens our results.

Overall, the event study around the 2016 presidential election shows that investors perceived Trump's victory and the associated threat of restrictions on skilled immigrants as a negative shock for firms heavily reliant on the H-1B program. The sharp decline in their stock prices during the short event window, when firm fundamentals were unlikely to have changed materially, points to a potential causal link from skilled labor to firm value. At first glance, this immediate market reaction may seem at odds with our broader finding of a sluggish response to the value created by H-1B workers. However, Trump's vocal opposition to immigration, including explicit threats to eliminate the H-1B program, likely raised investor awareness of its importance, prompting the swift market response following the election. Still, a short-term market reaction does not rule out a longer-term underreaction, just as markets may respond quickly to earnings news while still exhibiting post-earnings announcement drift. In this case, although the surprise election outcome delivered a negative shock to high H-1B firms and prompted an immediate market response, on average, the market continued to significantly undervalue these firms over extended periods of time, consistent with our main findings.

6 City and Firm Effects in Value Creation

In this section, we use information about the firms' locations to provide indirect evidence about the extent to which the excess returns documented in the previous section can be attributed to the firms' abilities to attract talent. The first set of tests, reported in subsections 6.1 and 6.2, identifies the firm-specific and urban attributes that are associated with H-1B hiring. We then estimate the extent to which these attributes predict stock returns in our sample period. The second set of tests, reported in subsection 6.3, explore whether the benefits of attracting and utilizing H-1B workers are amplified by the hiring patterns of its local peers. As described in the urban economics literature, H-1B workers may be more productive if they are located within talent clusters, suggesting that the return premium experienced by high H-1B firms might be higher in locations with high H-1B peers.

6.1 City-level Determinants of H-1B Hiring and Value Creation

The analysis so far has established that a relatively small number of cities attract a large fraction of the H-1B workers (Figure 2). In this subsection, we dig deeper into specific city-level characteristics that may be associated with H-1B employment. The primary goal is to identify city attributes that affect a firm's ability to attract talent, but that otherwise, are not likely to be directly related to firms' growth opportunities.

The first such variable is whether a city (defined as a core-based statistical area, CBSA) is home to an "Immigrant Integration Office."[19] We manually match locations of immigrant integration offices to our sample of firm headquarter cities, creating an indicator variable, *ImmigrantOffice*, that equals one if a firm's headquarter city has an immigrant integration office in the current year, and zero otherwise. In our sample, the percentage of firms with established immigrant integration offices in the headquarter cities steadily increases from around 23% in 2008 to above 55% in 2020. Second, we consider ethnic diversity. Using county-level population data from the U.S. Census 2010 5-year estimates (see details in Section 2), we construct *AsianRatio* as the percentage of Asians (number of Asian residents scaled by total population) in the CBSA where the firm is headquartered.[20] Our assumption—at least as a first approximation—is that these variables capture an element of cross-sectional variation in H-1B hiring that is unrelated to differences in growth opportunities arising from factors other than the types of people the firm is likely to hire. We provide supporting evidence for this identifying assumption later in Section 6.3.

Table 11 reports regressions of firms' H-1B intensity on firm and industry characteristics as well as the above-mentioned headquarter city attributes during the concurrent fiscal year. Panel A reports Probit regressions using the full firm-year sample (including all firms with and without H-1B petitions), where the dependent variable is a binary indicator of whether the firm has filed at least one H-1B petition in a fiscal year. In Panel B, we run panel regression using only the firm-year sample with H-1B petitions, where the dependent variable is a continuous variable of firms'

[19]We obtain a list of 22 city offices for immigrant integration (with non-missing establishing year) from Appendix A of the report "Opening Minds, Opening Doors, Opening Communities: Cities Leading for Immigrant Integration", prepared by the USC Center for the Study of Immigrant Integration. `https://kingcounty.gov/~/media/elected/executive/equity-social-justice/2017/USC-ReportOfficesofImmigrantIntegration.ashx?la=en`.

[20]According to USCIS data reports for 2019 fiscal year, more than 85% of H-1B petitions are filed by Asian applicants. `https://www.uscis.gov/sites/default/files/document/data/h-1b-petitions-by-gender-country-of-birth-fy2019.pdf`

H1BIntensity. We include year fixed effects, industry fixed effects (Fama-French 49 industries), and industry$\times$year fixed effects, respectively, and cluster standard errors by firm.

Regarding firm characteristics, we find that H-1B hiring is positively associated with firm size and profitability. Likewise, organization capital (*OrgCap*) and R&D capital (*RDC*) are positive determinants of H-1B applications. The predictions of most firm-level determinants are aligned between the Probit and continuous estimations, but not always (e.g., book-to-market ratio).

On the city side, the concentration of Asian residents (*AsianRatio*) is the strongest city-level determinant, and in the continuous models (Columns (4)–(6)), it is the strongest factor among *all* variables, including firm characteristics. Doubling the percentage of Asians in a city—equivalent to moving from Portland, OR (5.6%) to Seattle, WA (11%)—is associated, on average, with a $20-30\%$ increase in H-1B applications. The presence of an immigrant integration office (*ImmigrantOffice*) also contributes explanatory power, though the effect is stronger in the discrete choice models (Columns (1)–(3)).

The average city-level book-to-market ratio (*CityBM*) is generally not significant. However, city-level R&D capital (*CityRDC*), aggregated across a firm's local peers, is positively related to a firm's propensity to hire H-1B workers.[21] Note the near-equivalent coefficients between a firm's own R&D capital and that involving surrounding firms. In each case, the estimates suggest that, with respect to H-1B hiring patterns, firms are equally sensitive to increases in their own R&D as well as to those of their local neighbors.

6.2 H-1B Hiring Decomposition

Given the results of Table 11, we are now in a position to estimate the extent to which the various components of *expected* H-1B hiring forecast future stock returns. To do this, we use the

[21] Following Dougal, Parsons, and Titman (2022), we calculate *CityBM* and *CityRDC*, defined as the average book-to-market ratio and R&D capital (both adjusted by industry average using 2-digit SICCD), respectively, across all public firms in each core-based statistical area (CBSA). We require at least 5 public firms per CBSA per fiscal year to compute these city averages.

model in Table 11 to decompose firms' H-1B hiring intensity into expected and residual components. Specifically, at the end of each fiscal year, we run the following cross-sectional regression:

$$\begin{aligned} H1BIntensity = &\ logMarketCap + logBM + AG + OperProfit + OrgCap + RDC \\ &+ ImmigrantOffice + AsianRatio + CityBM + CityRDC \\ &+ Industry\ Fixed\ Effects + \epsilon \end{aligned} \tag{1}$$

All variables are measured in the same fiscal year *t*. We use coefficient estimates in year *t* to decompose *H1BIntensity* into two expected components along with a residual component. *ExpectedH1BFirm* is the expected component based on the intercept, *logMarketCap*, *logBM*, *AG*, *OperProfit*, *OrgCap*, *RDC*, and industry fixed effects. *ExpectedH1BCity* is the expected component based on *ImmigrantOffice*, *AsianRatio*, *CityBM*, and *CityRDC*. The residual component, *ResidualH1B*, is the difference between the actual *H1BIntensity* and the sum of the two expected components. We then run Fama-MacBeth cross-sectional regressions of monthly stock returns on the three components.

Table 12 reports the results. The coefficients on the expected component based on firm and industry attributes (*ExpectedH1BFirm*) are not reliably different from zero in four out of the five columns. In contrast, the residual component (*ResidualH1B*), which captures H-1B hiring unexplained by firm or city characteristics, is statistically significant in four of the five subsequent years. Finally, the expected component based on headquarter city attributes (*ExpectedH1BCity*) is generally the strongest forecasting variable, both economically and statistically.

These results have several implications. First, if H-1B hiring forecasts stock returns due to a correlation with unobserved firm and industry prospects, these opportunities appear orthogonal to conventional measures of firms' growth potential. Second, because city attributes are likely orthogonal to managers' private information, the private information channel cannot explain the excess returns associated with city characteristics. Lastly, the estimated coefficients of the city and residual components are of similar magnitude, suggesting that the market underreacts equally to the future value created by H-1B workers hired for no observable reason and those whose hiring can be explained by headquarter city attributes.

6.3 Differential Impact of H-1B Hiring Across Cities

To further extend these city-level results, we explore whether the effects of a firm's H-1B hiring patterns on stock returns are amplified by the hiring patterns of its local peers. There are several reasons why local H-1B hiring might matter for an individual firm. First, foreign talent may work more productively in communities with a higher concentration of similar workers, generating local knowledge spillovers that enhance firm value. Second, immigrant-rich cities may be more attractive places to live and work, allowing firms to recruit higher-quality H-1B candidates. Third, these cities may host more productive or high-growth firms that are inherently better positioned to attract top talent. While the third channel reflects firm fundamentals driving both H-1B hiring and stock performance, the first two emphasize a direct contribution of skilled labor to firm value.

To test this, we re-estimate the specification from the first column of Table 4 on different sub-samples stratified by *city-level* H-1B hiring, *H1BIntensityCity*, defined as the logarithm of total H-1B applications made by firms headquartered in the city scaled by lagged city-level total employment.[22] Panel A of Table 13 reports the results. The first three columns show results for cities in the lowest, middle, and highest terciles, ranked by *H1BIntensityCity* in the prior fiscal year. Both the magnitude and statistical significance of the *H1BIntensity* coefficients increase monotonically with city-level H-1B hiring. In cities in the lowest and middle terciles, there is no significant evidence that firm-level H-1B hiring predicts future stock returns. In contrast, the coefficient on *H1BIntensity* is substantially larger and statistically significant for firms headquartered in the highest H-1B cities (0.117, $t = 2.85$).

The final column in Panel A formalizes these comparisons by including an interaction term

[22]Note that a city's average (and rank of) H-1B hiring intensity can vary from year to year.

between firm-level and city-level H-1B hiring intensities. Notably, the coefficient on *H1BIntensityCity* alone is statistically indistinguishable from zero, indicating that city-level H-1B hiring does not, by itself, predict stock returns. This finding supports our identifying assumption that city-level attributes that are attractive to foreign professionals are not systematically correlated with firm fundamentals. In contrast, the coefficients on both *H1BIntensity* and the interaction term *H1BIntensity*×*H1BIntensityCity* are positive and significant, with similar magnitudes. When expressed in standard deviations (the coefficients are all normalized), the effect on a firm's future returns from H-1B hiring roughly doubles with each standard deviation increase in city-level H-1B hiring.[23]

Panel B of Table 13 repeats the same specification, but with progressively longer lags of when firms and cities are ranked by H-1B hiring. Interestingly, while the firm's own H-1B hiring is less reliable at higher lags, the interaction term between firm-level and city-level H-1B hiring maintains significance, and actually gets stronger with longer lags. These results suggest that markets systematically underappreciate the *future* wealth created by firms that hire large numbers of H-1B workers, particularly when they are surrounded by neighboring firms doing the same.

The null effect of city-level H-1B hiring alone on future stock returns indicates that firms in immigrant-rich cities are not, on average, fundamentally different, which supports our identifying assumption. However, the fact that city-level H-1B hiring amplifies the return effects of firm-level hiring supports the idea of local knowledge spillovers and/or stronger talent pools in these cities. Another possible mechanism for the interaction effect is labor market liquidity: in cities with many H-1B workers, firms can more easily recruit H-1B workers initially employed by other local firms, thanks to the larger available labor pool. Although this mechanism differs from knowledge spillovers or stronger talent pools, all these channels point to a causal role of H-1B workers in

[23]Note that the interaction term *H1BIntensity*×*H1BIntensityCity* reflects a combination of: (1) variation in firm-level H-1B hiring within cities (or within cities with similar average H-1B hiring), and (2) variation in city-level H-1B hiring among firms with similar H-1B intensities. As it turns out, both sources of variation concentrate in the middle and bottom of the respective distribution. That is, in the lowest and middle terciles of H-1B cities, there are plenty of both low and middle H-1B firms. The reverse also holds; among firms with low or moderate H-1B intensities, we see considerable variation in city-level H-1B hiring in their headquarter cities. What we do *not* see, however, is a substantial number of high H-1B firms headquartered in cities in the lowest tercile of city-level H-1B hiring.

enhancing firm value. In all cases, these findings underscore the direct contribution of skilled labor to firm value.

Panel C of Figure 3 visually illustrates these return patterns. The double-sorted figure lends itself to a convenient interpretation. Starting with the black dashed line—low H-1B firms in cities with low average H-1B hiring—as a benchmark, we observe no abnormal stock performance. The blue dashed line, which reflects low H-1B firms in high H-1B cities, suggests that moving to a high H-1B city matters somewhat, but the effect is relatively small, consistent with our identifying assumption that firms located in immigrant-populated cities are not fundamentally different from others. More important is the firm's own H-1B hiring policy: the spread between the green solid line (high H-1B firms in low H-1B cities) and black dashed line more than doubles the blue-black spread. Most striking, however, is the red solid line (high H-1B firms in high H-1B cities), which shows the best performance by far, with shareholder value increasing by 40% on an industry-adjusted basis over the sample period.

7 Conclusion

Firms can be characterized by a number of attributes that either directly or indirectly affect their values. The most visible— and perhaps easiest to value—are tangible assets, such as property and equipment. Less tangible assets, like patents and brands, tend to be more difficult to value, and perhaps the most challenging is assessing the value that can be attributed to a firm's superior talent. How do we measure the extent to which Firm A has more creative or productive employees than Firm B? And if a firm does have a more talented workforce, does it capture most of the benefit, or do the employees capture the lion's share via higher wages?

While we cannot explicitly quantify the market value of a firm's workforce, we present indirect evidence suggesting that the "people side" of a firm's organization can contribute substantially to its value. Specifically, we show that firms with a comparative advantage in attracting and/or developing foreign-born talent realized significant excess returns relative to their industry peers following the expansion of the H-1B program. The magnitudes are substantial. We document excess industry-adjusted returns associated with the intense hiring of H-1B visa holders between 2-3% per year. Given that these abnormal returns last for at least five years, superior talent appears capable of explaining perhaps 10-15% of the increase in the market capitalization of high H-1B firms in our sample period. While we are not the first to explore the empirical linkage between organization capital and stock performance, building on seminal studies by Lev and Radhakrishnan (2005) and Eisfeldt and Papanikolaou (2013), our paper provides a new approach for identifying the value created by skilled workers.

The key identification challenge stems from the endogeneity of hiring decisions, since managers anticipating favorable prospects would likely add skilled labor in advance. Although this idea may sound intuitive, it relies critically on the assumption that managers systematically possess *private and informative* signals that are not incorporated into stock prices. In fact, a large body of literature suggests that high investment in physical assets forecasts low, rather than high, returns.[24] Hence, if intensive hiring of skilled foreign labor reflects managerial optimism, finding a positive relation with future returns (as we do) would provide an interesting contrast with prevailing studies. An alternative interpretation is that the stock market simply failed to fully apprehend the importance of a particular class of workers, and that as the productivity enhancements became apparent through fundamentals (e.g., earnings), it eventually learned.

There are two broad mechanisms that permit shareholders to capture surplus associated with skilled foreign labor. One is monopsony power, whereby firms can successfully offer below-market wages to H-1B workers, perhaps due to segmentation or other frictions. Another is due to interactions, spillovers, or other externalities that boost productivity, but without a (total) offset in labor costs. Unfortunately, because identifying spillovers empirically is notoriously difficult (Manski, 1993), we can only offer indirect evidence. Still, when considered as an

[24] See, for example, Titman, Wei, and Xie (2004), Cooper, Gulen, and Schill (2008), Fama and French (2015), and Hou, Xue, and Zhang (2015).

ensemble, multiple lines of evidence point toward interactions/spillovers playing at least some role in the observed patterns of stock returns and firm performance:

1. The relation between H-1B visas and stock returns is highly non-linear.

2. H-1B workers tend to work primarily in technological industries, and we know from the labor literature that idea-based spillovers are more likely to occur in innovative sectors.

3. Excess returns for high H-1B firms are largest in high-STEM industries.

4. Excess returns for high H-1B firms are largest in cities with a large congregation of other H-1B employees outside the firm of interest. This is true even outside the firm's own industry.

In each of these cases, it is clear how spillovers, either within firms or between them, could explain the observed patterns. At the same time, it is less obvious why monopsony power would vary in the same way—for example, why a firm employing 100 H-1B workers would have more per-worker bargaining power in wages compared to one employing 50. Nevertheless, we regard such distinctions as interesting and fruitful potential areas for future research.

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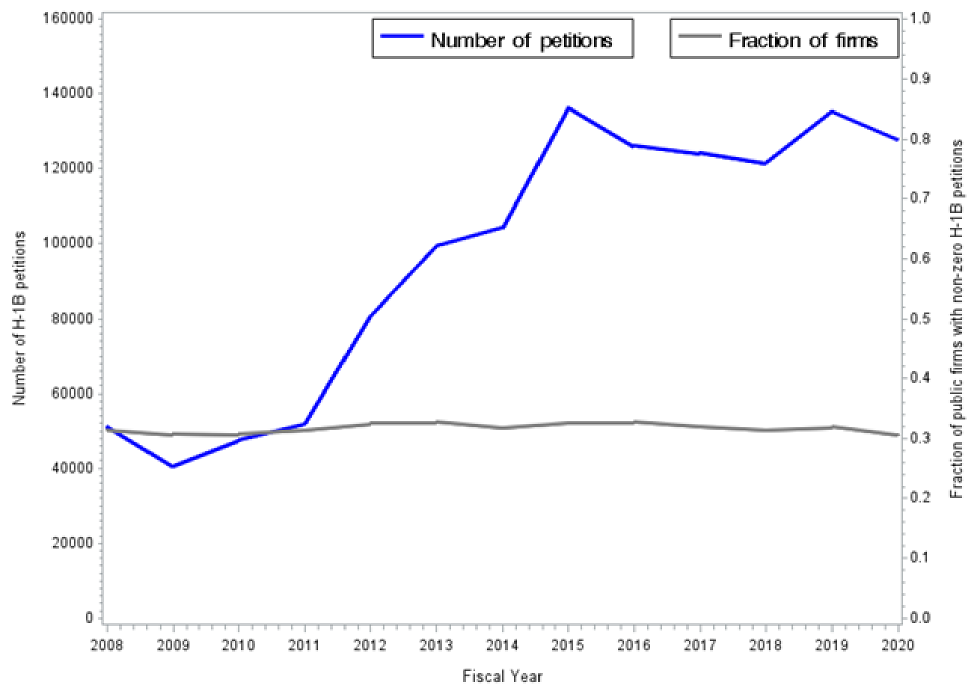
Figure 1: H-1B Petitions, Firms, and Occupations

In Panel A, the blue line plots the number of H-1B petitions per fiscal year from 2008 to 2020, and the grey line plots the fraction of public firms with non-zero H-1B petitions over all CRSP firms. Panel B plots a pie chart of H-1B petitions by occupation group in fiscal year 2020.

Panel A: Number of H-1B petitions and fraction of firms



Panel B: Petitions by occupation in fiscal year 2020

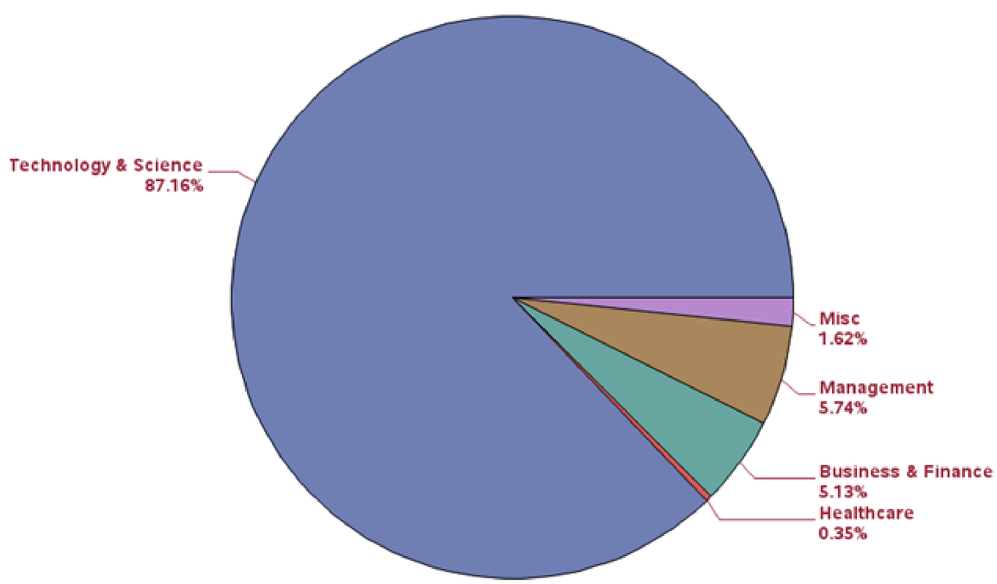


Figure 2: Geographic Distribution of H-1B Petitions

This figure plots the total number of H-1B petitions filed by firms located in each core-based statistical area (CBSA) over 2008 to 2020 fiscal years.

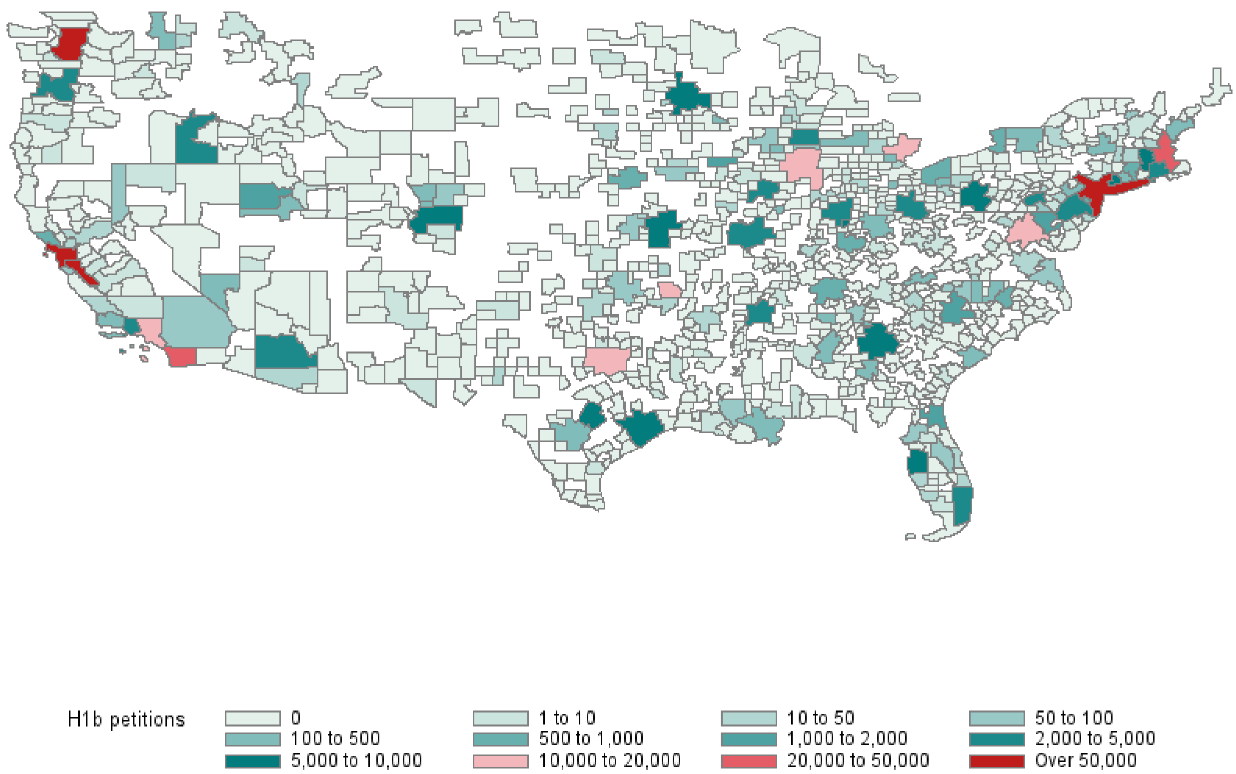
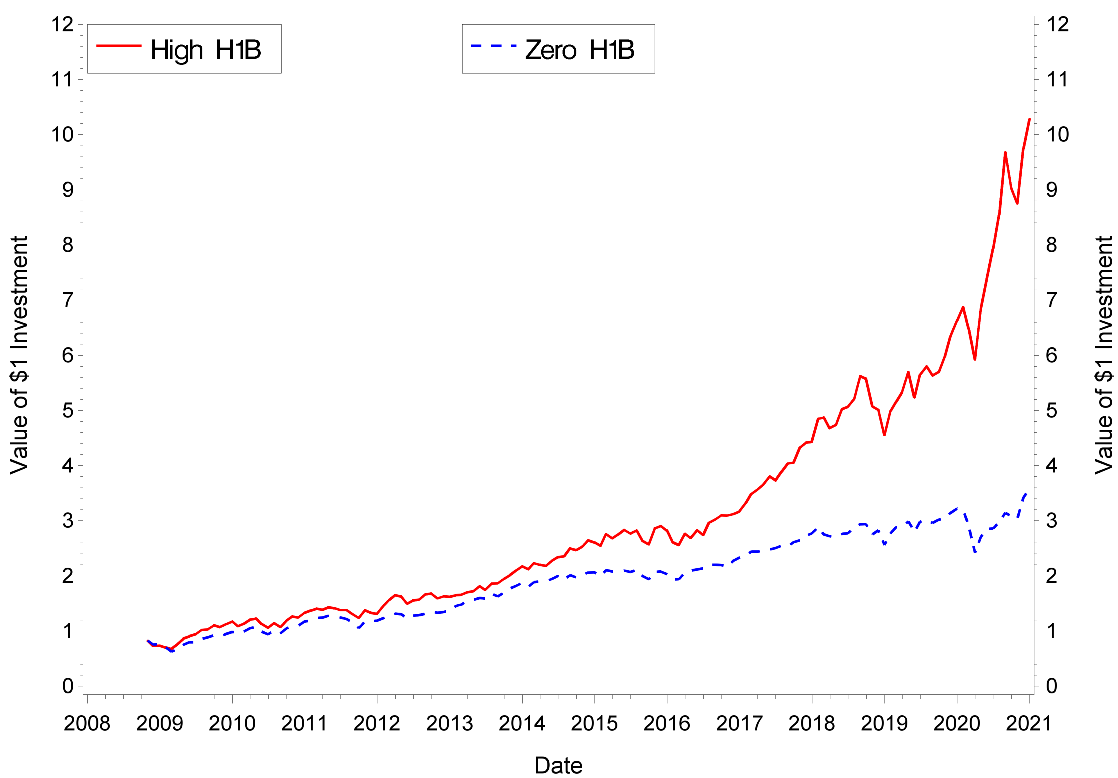


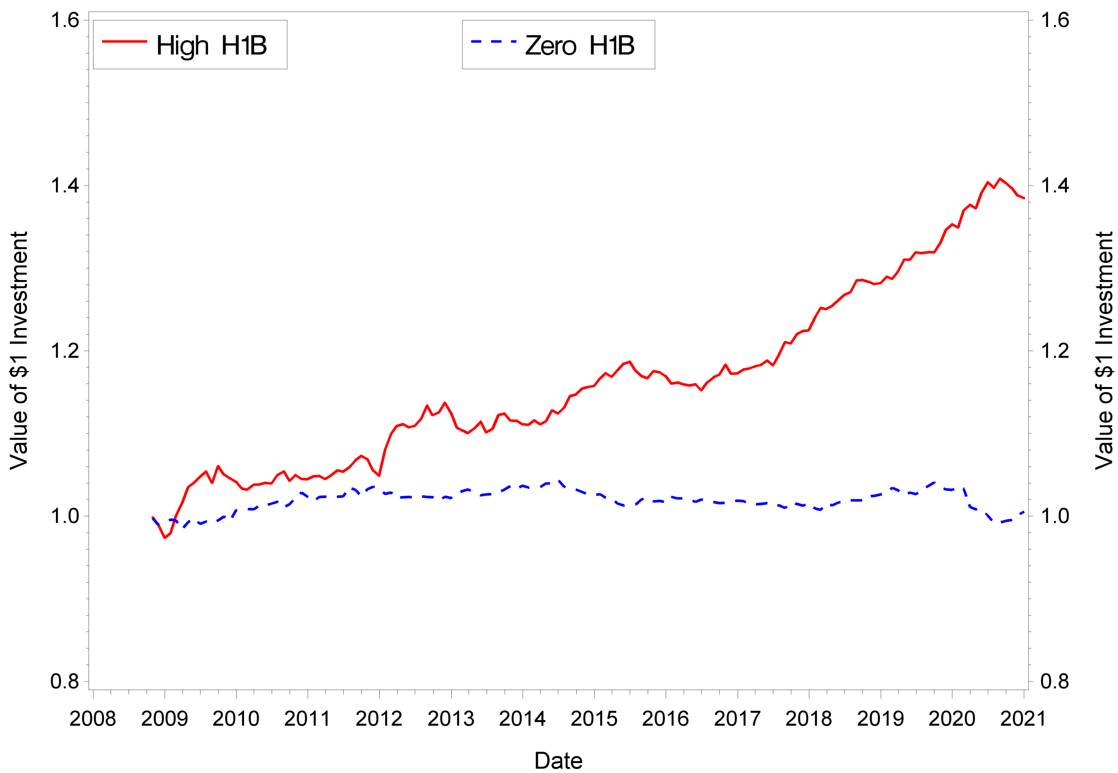
Figure 3: Value of $1 Investment in H-1B Portfolios

This figure plots the cumulative value of $1 investment in portfolios sorted by H-1B intensity. At the end of each fiscal year *t*, firms are ranked into five portfolios (Low, 2, 3, 4, and High) by H-1B intensity. Firms with no H-1B petition are grouped into the Zero portfolio. The portfolios are rebalanced at the end of fiscal year $t + 1$. We calculate the cumulative value of $1 investment in each portfolio during the investment period of 2008/10 to 2020/12. Panel A compares the cumulative values of the High and Zero portfolios based on raw stock returns, and Panel B uses industry-adjusted returns (based on Fama-French 49-industry classifications). Panel C compares the cumulative values of four portfolios, double-sorted by H-1B intensity at the firm and city level. High cities are those ranked in the top tercile by city-level H-1B hiring intensity, and other cities are those in the middle and bottom terciles.

Panel A: Cumulative value using raw returns



Panel B: Cumulative value using industry-adjusted returns



Panel C: Cumulative value across cities (using industry-adjusted returns)

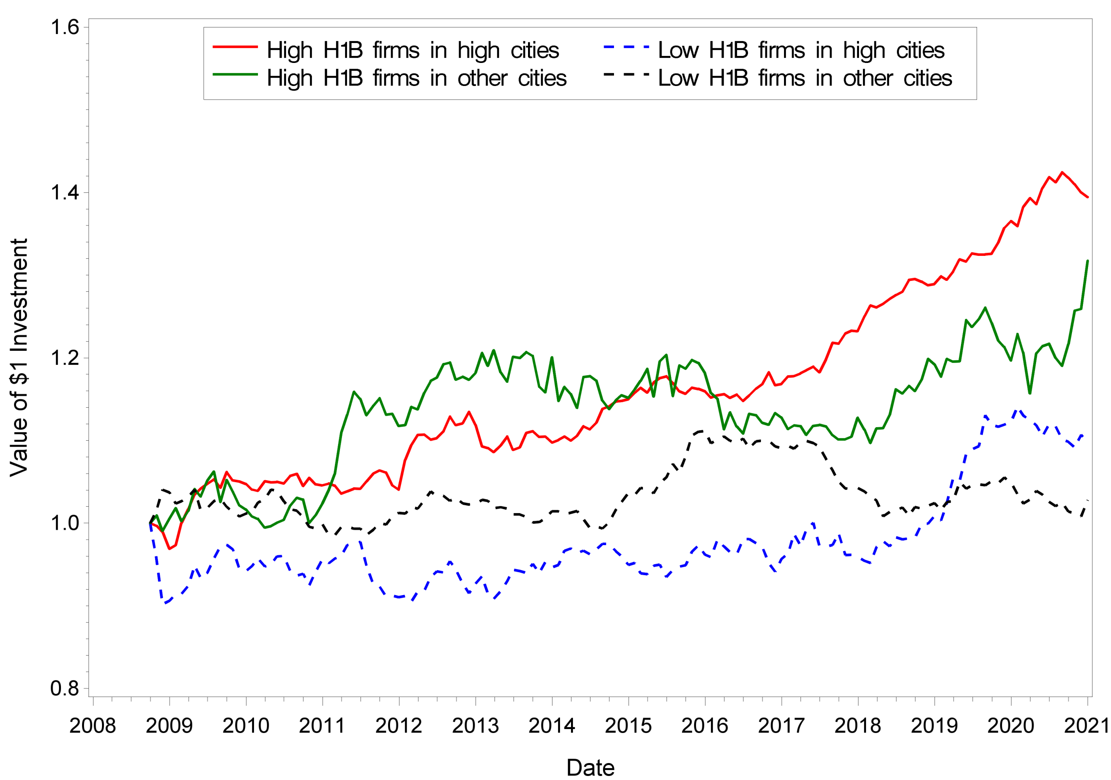
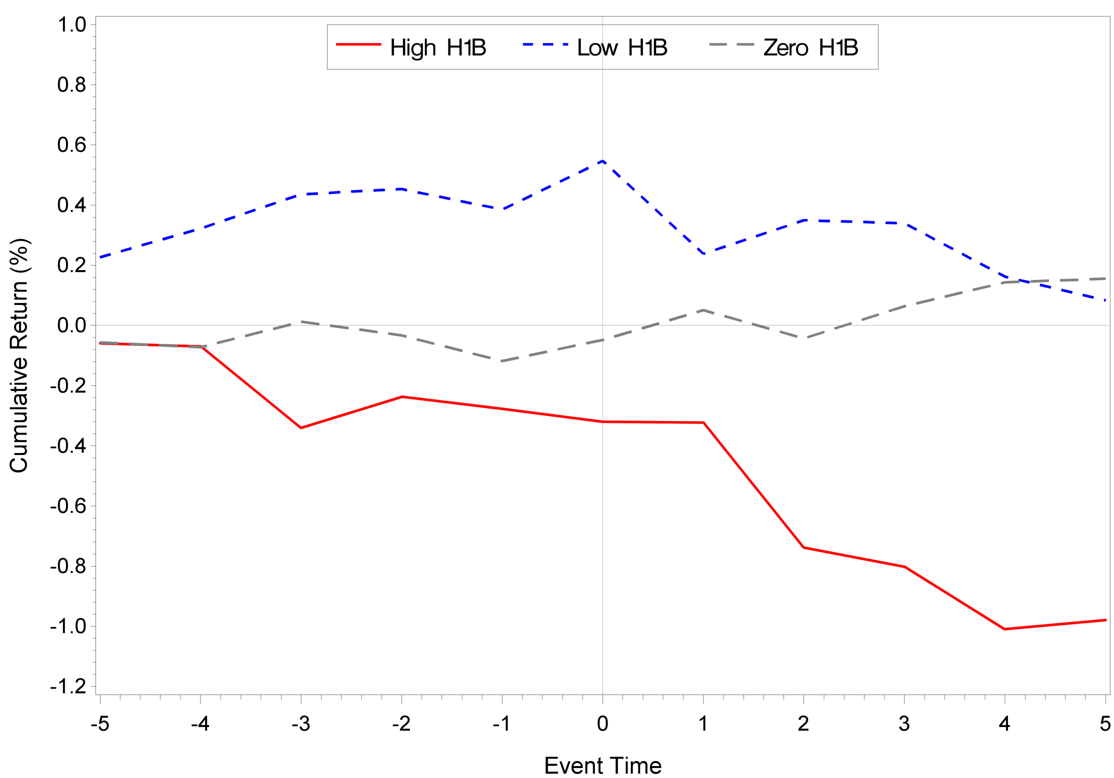


Figure 4: Event Study Around the Presidential Election of 2016

This figure plots the returns of H-1B portfolios around the presidential election of 2016. The election occurred on November 8, 2016, which we designate as the event date (t). We track cumulative portfolio returns over an 11-day window spanning 5 trading days before and 5 trading days after the election, from November 1 ($t-5$) to November 15 ($t+5$). The High, Low, and Zero H-1B portfolios are constructed following the methodology in Table 3. Panel A plots the cumulative portfolio returns using industry-adjusted returns. Panel B presents a robustness check that additionally controls for location effects specific to New York and California. For firms in these two states, we first regress the value-weighted average returns of all New York-based firms (and separately, all California-based firms) on industry average returns. We then subtract the residuals from these regressions, which capture location-specific returns orthogonal to industry performance, from the industry-adjusted returns of firms in each respective state.

Panel A: Cumulative industry-adjusted returns



Panel B: Further adjusting for New York and California location effects

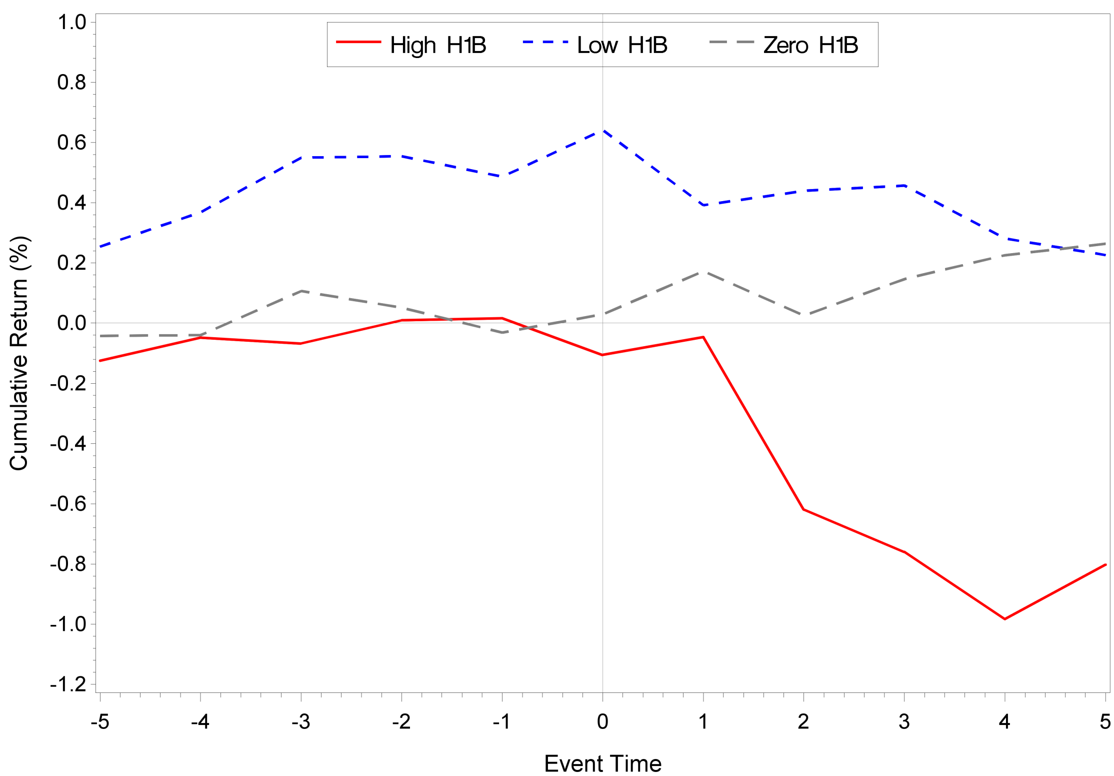


Table 1: Summary Statistics

This table reports summary statistics of firms' H-1B intensity measures and other characteristics. Panel A reports the statistics for the firm-year sample with at least one H-1B petition, and Panel B for the firm-year sample with zero H-1B petition. *H1B* is the count of a firm's H-1B petitions per fiscal year. *H1BIntensity* is the logarithm of H-1B petitions over total employee ratio. Other firm characteristics include the average wage paid for H-1B workers (*Wage for H-1B workers*), market capitalization (*MarketCap*), book-to-market ratio (*BM*), total employees (*EMP*), asset growth (*AG*), operating profitability (*OperProfit*), organization capital (*OrgCap*), R&D capital (*RDC*), sales growth (*SalesGrowth*), earnings growth (*EarningsGrowth*), and R&D expenses growth (*R&DGrowth*). All variables are winsorized at the top and bottom 1% by fiscal year. The sample period is 2008 to 2020 fiscal years.

Panel A: Firm-year sample with at least one H-1B petition

Variable	N	Mean	Std	10^{th} Pctl	25^{th} Pctl	50^{th} Pctl	75^{th} Pctl	90^{th} Pctl
H1B	15,383	46.66	159.58	1	2	5	21	88
H1BIntensity	13,124	0.36	1.6	-1.67	-0.65	0.3	1.48	2.49
Wage for H-1B workers ($)	15,383	94,539	26,082	64,589	77,250	91,817	108,000	127,240
MarketCap ($m)	13,196	8,530	21,111	94	341	1,354	5,655	21,732
BM	12,657	0.61	0.7	0.12	0.23	0.43	0.75	1.18
EMP (,000s)	13,140	14.82	32.9	0.16	0.58	2.7	11.3	40
AG	12,605	0.12	0.35	-0.15	-0.03	0.05	0.16	0.40
OperProfit	12,699	0.16	0.61	-0.28	0.06	0.2	0.34	0.53
OrgCap	12,641	0.74	0.69	0.00	0.23	0.58	1.06	1.64
RDC	13,196	0.19	0.32	0	0	0.05	0.26	0.55
SalesGrowth	12,600	0.08	0.29	-0.16	-0.02	0.06	0.16	0.32
EarningsGrowth	12,601	0.004	0.14	-0.11	-0.03	0	0.03	0.11
R&DGrowth	12,605	0.05	0.19	-0.09	0	0	0.11	0.27

Panel B: Firm-year sample with zero H-1B petition

Variable	N	Mean	Std	10^{th} Pctl	25^{th} Pctl	50^{th} Pctl	75^{th} Pctl	90^{th} Pctl
MarketCap ($m)	34,423	2,999	10,832	26	78	338	1,588	5,507
BM	32,725	0.89	1.01	0.18	0.35	0.65	1.03	1.69
EMP (,000s)	34,086	6.53	19.81	0.05	0.16	0.8	4.19	14.13
AG	32,405	0.1	0.36	-0.17	-0.04	0.04	0.14	0.36
OperProfit	32,833	0.08	0.71	-0.41	0.01	0.16	0.29	0.48
OrgCap	32,559	0.56	0.7	0	0.05	0.29	0.82	1.48
RDC	34,414	0.13	0.35	0	0	0	0.07	0.40
SalesGrowth	32,327	0.06	0.31	-0.19	-0.04	0.04	0.14	0.30
EarningsGrowth	32,362	0.004	0.16	-0.11	-0.02	0	0.03	0.10
R&DGrowth	32,415	0.02	0.17	-0.06	0	0	0	0.16

Table 2: Characteristics of Firms Ranked by H-1B Intensity

This table reports the characteristics of firms ranked by H-1B intensity. At the end of each fiscal year, firms are ranked into five portfolios (Low, 2, 3, 4, and High) based on H-1B intensity. Firms with no H-1B petition are grouped into the Zero portfolio. For each portfolio, we calculate the equal-weighted averages of size-related variables, including the ranking variable (*H1BIntensity*), the count of H-1B petitions (*H1B*), market capitalization (*MarketCap*), total employees (*EMP*), and average wage paid to H-1B workers (*Wage for H-1B workers*) during the same fiscal year; we also calculate the value-weighted average of firms' book-to-market ratios (*BM*). β is the portfolio's market beta estimated by the market model, $R_P - R_f = \beta \times (MKT{-}R_f)$, using monthly portfolio returns in the following fiscal year after ranking, estimated over the whole sample period. All variables, except β, are winsorized at the top and bottom 1% by fiscal year. The sample period is 2008 to 2020 fiscal years.

Portfolios	*H1BIntensity*	*H1B*	*MarketCap* ($m)	*EMP*(,000s)	*Wage for H-1B workers* ($)	*BM*	β
Zero		0.00	3,065	6.59		0.58	0.99
Low	-1.88	4.91	10,114	30.89	90,834	0.45	0.98
2	-0.43	8.40	5,454	12.34	91,922	0.51	1.03
3	0.30	19.39	6,884	12.38	94,154	0.54	0.86
4	1.24	44.21	8,358	10.45	94,909	0.48	1.03
High	2.61	151.88	12,840	8.49	100,347	0.32	1.07
High–Low	4.49***	146.97***	2,726	-22.41***	9,513***	-0.13***	0.09*
	(44.31)	(4.47)	(1.38)	(-22.30)	(4.67)	(-6.07)	(1.72)
High–Zero		151.88***	9,775***	1.90**		-0.26***	0.08
		(4.58)	(3.31)	(2.42)		(-28.43)	(1.57)

Table 3: Returns of H-1B Intensity Portfolios

This table examines returns of portfolios sorted on H-1B intensity. At the end of each fiscal year t, firms are ranked into five portfolios (Low, 2, 3, 4, and High) based on *H1BIntensity*. Firms with no H-1B petition are grouped into the Zero portfolio. The portfolios are rebalanced at the end of fiscal year $t+1$. In Panel A, we calculate the value-weighted average annual portfolio returns in each of the 5 years after ranking. In Panel B, we form portfolios based on firms' *H1BIntensity* at the end of fiscal year t, hold the portfolio for 12 months, and rebalance portfolios at the end of fiscal year $t+1$. We regress the time series of monthly portfolio returns on the CAPM, the Fama-French 5-factor model (FF5), the Fama-French 5-factor model plus a momentum factor (FF6), the $q5$ model of Hou, Mo, Xue, and Zhang (2021), and the behavioral model of Daniel, Hirshleifer, and Sun (DHS, 2020) to estimate monthly alphas. We estimate the annualized portfolio returns and alphas by multiplying the monthly estimates by 12. All returns are industry-adjusted by the value-weighted industry average in each month (using Fama-French 49-industry classifications). The sample period is 2008/10 to 2020/12.

Panel A: Annualized (industry-adjusted) portfolio returns (%) over 5-year horizon

Portfolios	N firms	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Zero	2957.2	-0.37	-0.06	-0.17	-0.50	-0.70
		(-0.85)	(-0.13)	(-0.40)	(-1.40)	(-1.45)
Low	202.5	0.11	-0.44	-0.51	-0.84	-0.58
		(0.14)	(-0.47)	(-0.52)	(-0.71)	(-0.40)
2	201.9	0.86	0.90	-0.60	1.06	-2.03
		(0.94)	(1.38)	(-0.47)	(0.94)	(-1.22)
3	201.7	-1.22	-1.44	0.32	0.16	0.44
		(-1.92)	(-1.54)	(0.38)	(0.19)	(0.31)
4	202.0	-0.79	-0.13	-1.52	0.26	0.02
		(-0.79)	(-0.10)	(-1.11)	(0.22)	(0.01)
High	201.4	2.06	1.19	1.98	1.80	1.93
		(4.08)	(1.37)	(3.11)	(3.43)	(3.13)
High–Low		1.95*	1.63	2.49*	2.64**	2.51
		(2.00)	(1.36)	(2.16)	(2.43)	(1.80)
High–Zero		2.43***	1.25	2.14**	2.30***	2.63***
		(3.08)	(0.99)	(2.23)	(3.41)	(3.61)

Panel B: Annualized (industry-adjusted) portfolio returns and alphas (%) over 1-year horizon

	Zero	Low	2	3	4	High	High–Low	High–Zero
Average return	-0.36	-0.12	0.96	-1.20	-1.08	2.28	2.40**	2.64**
	(-1.02)	(-0.19)	(1.02)	(-1.02)	(-1.01)	(2.87)	(2.09)	(2.60)
CAPM alpha	-0.60	-0.36	0.60	0.24	-1.08	2.04	2.40**	2.64**
	(-1.24)	(-0.45)	(0.64)	(0.22)	(-0.82)	(2.72)	(2.06)	(2.52)
FF5 alpha	-0.36	-0.60	-0.24	-0.24	-0.48	2.04	2.64**	2.40***
	(-1.18)	(-0.70)	(-0.22)	(-0.23)	(-0.50)	(2.82)	(2.37)	(2.65)
FF6 alpha	-0.36	-0.60	-0.24	-0.12	-0.48	1.92	2.52**	2.28***
	(-1.15)	(-0.68)	(-0.28)	(-0.16)	(-0.51)	(2.86)	(2.31)	(2.65)
$q5$ alpha	0.00	-0.36	0.84	0.00	-2.28	1.80	2.04**	1.80**
	(-0.07)	(-0.44)	(0.66)	(-0.01)	(-1.93)	(2.36)	(2.00)	(2.04)
DHS alpha	-0.36	-0.60	0.60	0.12	-1.32	2.28	2.88**	2.76***
	(-0.98)	(-0.76)	(0.51)	(0.06)	(-0.98)	(2.93)	(2.59)	(2.79)

Table 4: Fama-MacBeth Return Regression

This table reports results of monthly cross-sectional regressions of stock returns on H-1B intensity. The dependent variable is monthly stock returns (in excess of the risk-free rate) in fiscal year *t*. The main variable of interest is firms' *H1BIntensity* in fiscal year $t–n$, where *n* equals 1 to 5. *ZeroH1B* is an indicator that equals one if a firm has no H-1B petition in that fiscal year, and zero otherwise. We control for market capitalization (*logMarketCap*), book-to-market ratio (*logBM*), asset growth (*AG*), operating profitability (*OperProfit*), and organization capital (*OrgCap*) in fiscal year $t–n$ (the same fiscal year as H-1B petitions), as well as market beta (*Beta*), momentum (*Ret (t-12, t-2)*) and reversal (*Ret (t-36, t-13)*) variables at the previous month end. We include industry dummies (using Fama-French 49-industry classifications) to control for industry average returns. All non-indicator independent variables are winsorized and standardized with zero mean and unit variance. Newey-West corrected *t*-statistics (with 12 lags) are reported in the parentheses. The sample period is 2008/10 to 2020/12.

	Dependent variable = Monthly returns in fiscal year *t*				
	n = 1	*n* = 2	*n* = 3	*n* = 4	*n* = 5
H1BIntensity (t-n)	0.083***	0.075**	0.067**	0.048*	0.077**
	(3.38)	(2.51)	(2.15)	(1.84)	(2.15)
ZeroH1B (t-n)	-0.053	-0.058	-0.007	-0.093**	-0.036
	(-1.25)	(-1.24)	(-0.12)	(-2.28)	(-0.77)
logMarketCap (t-n)	-0.092	-0.081	-0.025	-0.011	0.005
	(-0.86)	(-0.67)	(-0.24)	(-0.09)	(0.03)
logBM (t-n)	0.037	0.022	0.061	0.105	0.018
	(0.43)	(0.24)	(0.76)	(1.13)	(0.17)
AG (t-n)	-0.165***	-0.047	-0.040	0.030	-0.081
	(-4.35)	(-1.40)	(-0.79)	(0.66)	(-1.56)
OperProfit (t-n)	0.163**	0.180***	0.169***	0.148***	0.042
	(2.18)	(3.07)	(3.21)	(2.70)	(0.65)
OrgCap (t-n)	-0.044	-0.012	-0.032	-0.039	0.011
	(-0.86)	(-0.22)	(-0.53)	(-0.63)	(0.19)
Beta	0.074	-0.025	-0.022	0.023	0.029
	(0.47)	(-0.17)	(-0.14)	(0.13)	(0.15)
Ret (t-12, t-2)	-0.258	-0.086	-0.063	-0.073	-0.060
	(-1.39)	(-0.88)	(-0.61)	(-0.67)	(-0.50)
Ret (t-36, t-13)	-0.028	0.043	0.085	0.117	0.107
	(-0.22)	(0.49)	(0.91)	(1.06)	(0.88)
Industry F.E.	Yes	Yes	Yes	Yes	Yes
Adj. R^2	7.0%	6.7%	6.8%	7.0%	7.2%
Observations	422,545	378,279	328,657	282,746	240,698

Table 5: Fama-MacBeth Return Regression: Robustness Tests

This table presents various robustness checks of the main results from the monthly cross-sectional regressions of stock returns on H-1B intensity reported in Table 4. The dependent variable is monthly stock returns (in excess of the risk-free rate) in fiscal year *t*. The main variable of interest is firms' *H1BIntensity* in the previous fiscal year t–1. We control for the *ZeroH1B* indicator, market capitalization (*logMarketCap*), book-to-market ratio (*logBM*), asset growth (*AG*), operating profitability (*OperProfit*), and organization capital (*OrgCap*), all measured in fiscal year t–1 (the same fiscal year as H-1B petitions), as well as market beta (*Beta*), momentum (*Ret (t-12, t-2)*) and reversal (*Ret (t-36, t-13)*) variables at the previous month end. We examine robustness by including additional controls: R&D capital (*RDC*) and cash-based operating profitability (*CbOP*), as defined in Appendix A; the changes in total employees (*logEMP_chg*), defined as the difference between the logarithm of total employees in the current year and the logarithm of total employees in the previous year; *logH1B*, the logarithm of the total count of H-1B petitions; and *logEMP*, the logarithm of total employees. We include industry dummies (using Fama-French 49-industry classifications) to control for industry average returns. All non-indicator independent variables are winsorized and standardized with zero mean and unit variance. Newey-West corrected *t*-statistics (with 12 lags) are reported in the parentheses. The sample period is 2008/10 to 2020/12.

	Dependent variable = Monthly returns in fiscal year *t*									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	FF 17 industry classifications	Excluding NY and CA firms	Excluding FAANG stocks	Excluding top 10% H-1B firms	Excluding firms above NYSE 90th size pctl.	Leaving 3-month gap after H-1B disclosures	Ctrl. R&D Capital	Ctrl. cash-based operating profitability	Changes in total employees	Separating H-1B hiring and total employees
H1BIntensity (t-1)	0.096***	0.049**	0.078***	0.054**	0.089***	0.101***	0.077***	0.069**		
	(3.67)	(2.37)	(3.24)	(2.09)	(3.60)	(4.12)	(3.09)	(2.60)		
ZeroH1B (t-1)	-0.079	-0.024	-0.048	-0.028	-0.044	-0.021	-0.041	-0.043		0.109
	(-1.57)	(-0.51)	(-1.15)	(-0.63)	(-1.00)	(-0.46)	(-1.01)	(-0.96)		(1.30)
RDC (t-1)							0.122			
							(1.21)			
CbOP (t-1)								0.225***		
								(3.10)		
logEMP_chg (t-1)									-0.007	
									(-0.14)	
logH1B (t-1)										0.112**
										(2.07)
logEMP (t-1)										0.110
										(1.48)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	6.3%	7.9%	7.0%	7.1%	6.9%	7.0%	7.2%	7.0%	7.1%	7.1%
Observations	421,788	323,160	421,993	411,030	399,706	412,208	422,545	422,545	419,295	420,331

Table 6: Industry Effects

This table examines the return predictability of firm-level H-1B hiring intensity alongside industry-level H-1B hiring intensity and STEM prevalence. Industry-level H-1B intensity is defined as the logarithm of the ratio of aggregate H-1B petitions to aggregate employees across all firms in the corresponding industry. Industry STEM prevalence is measured as the percentage of workers in the industry employed in all STEM occupations. In Panel A, Fama-French 49 industries are sorted into terciles based on industry-level H-1B intensity; in Panel B, they are sorted by STEM prevalence. For each tercile, we calculate monthly value-weighted average portfolio returns (in percent) and the high-minus-low spread over the 12 months following portfolio formation, and estimate monthly alphas using CAPM, the Fama-French five-factor model (FF5), the FF5 model plus a momentum factor (FF6), the *q*5 model of Hou, Mo, Xue, and Zhang (2021), and the behavioral model of Daniel, Hirshleifer, and Sun (DHS, 2020). Panel C presents double sorts on firm-level H-1B intensity and industry-level STEM prevalence. Specifically, at the end of each fiscal year *t*, firms are ranked into five quintiles based on *H1BIntensity*, with firms having no H-1B petition placed in a separate Zero portfolio. To maintain sufficient portfolio population, particularly for high H-1B firms in low STEM industries, we collapse the Zero and quintile 1 portfolios into a Low group, quintiles 2 and 3 into a Mid group, and quintiles 4 and 5 into a High group. Independently, firms are assigned into three portfolios based on industry STEM prevalence. We then compute value-weighted monthly portfolio returns (in percent) for each double-sorted portfolio over the subsequent 12 months and report the corresponding high-minus-low spreads.

Panel A: Industry portfolios sorted by industry-level H-1B intensity

	Low Industry	Mid Industry	High Industry	High−Low Industry
Average return	0.95	1.07	1.14	0.19
	(2.11)	(2.41)	(2.76)	(1.18)
CAPM alpha	-0.22	-0.16	-0.02	0.20
	(-1.34)	(-1.31)	(-0.39)	(1.10)
FF5 alpha	-0.11	-0.07	0.02	0.13
	(-0.87)	(-0.53)	(0.36)	(0.95)
FF6 alpha	-0.13	-0.08	0.02	0.15
	(-1.07)	(-0.74)	(0.35)	(1.16)
*q*5 alpha	0.05	0.10	0.02	-0.03
	(0.38)	(0.83)	(0.32)	(-0.20)
DHS alpha	-0.10	-0.04	0.04	0.14
	(-0.64)	(-0.30)	(0.66)	(0.87)

Panel B: Industry portfolios sorted by industry-level STEM prevalence

	Low STEM	Mid STEM	High STEM	High−Low STEM
Average return	0.94	1.03	1.14	0.19
	(1.90)	(2.27)	(3.29)	(0.91)
CAPM alpha	-0.33	-0.20	0.11	0.43**
	(-2.17)	(-1.55)	(1.26)	(2.45)
FF5 alpha	-0.20	-0.14	0.06	0.26
	(-1.27)	(-1.06)	(0.86)	(1.33)
FF6 alpha	-0.22	-0.16	0.06	0.29
	(-1.57)	(-1.27)	(0.95)	(1.64)
*q*5 alpha	-0.05	0.05	0.15	0.20
	(-0.42)	(0.40)	(2.10)	(1.37)
DHS alpha	-0.17	-0.03	0.10	0.27
	(-1.07)	(-0.27)	(1.14)	(1.42)

Panel C: Double-sorted portfolios by firm-level H-1B intensity and industry-level STEM prevalence

Portfolios	Low STEM	Mid STEM	High STEM	High−Low STEM
Low	0.88	1.00	0.97	0.09
	(2.45)	(2.43)	(2.56)	(0.60)
Mid	0.82	0.90	0.84	0.02
	(1.82)	(2.00)	(2.40)	(0.09)
High	0.63	1.28	1.50	0.86*
	(1.08)	(2.81)	(3.72)	(1.87)
High−Low H1B	-0.25	0.28	0.53***	0.77
	(-0.55)	(1.30)	(2.64)	(1.65)

Table 7: H-1B Intensity and Operating Performance

This table reports results of annual panel regressions of firms' sales, earnings, and R&D expenses growth on past H-1B intensity. *SalesGrowth* is the logarithm of sales in year *t* minus the logarithm of sales in year *t* – 1. *EarningsGrowth* is the change in net income from year *t* – 1 to year *t* divided by total asset in year *t* – 1. *R&DGrowth* is the logarithm of R&D expenses in year *t* minus the logarithm of R&D expenses in year *t* – 1. The dependent variables are *SalesGrowth*, *EarningsGrowth*, and *R&DGrowth*, respectively, in each of the future 5 years (*t* + 1 to *t* + 5). The key independent variables are firms' H-1B intensity (*H1BIntensity*) in fiscal year *t*. We control for the corresponding dependent variable in fiscal year *t*, along with other controls including a *ZeroH1B* indicator, market capitalization (*logMarketCap*), book-to-market ratio (*logBM*), asset growth (*AG*), operating profitability (*OperProfit*), organization capital (*OrgCap*), and market beta (*Beta*), all measured in fiscal year *t* (the same fiscal year as H-1B petitions). We add industry×year fixed effects and cluster standard errors by firm. All non-indicator independent variables are winsorized and standardized with zero mean and unit variance. The sample period is 2008 to 2020 fiscal years.

Panel A: Sales Growth

	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
H1BIntensity (t)	0.017***	0.021***	0.022***	0.022***	0.014***
	(4.45)	(4.68)	(4.68)	(4.22)	(2.62)
SalesGrowth (t)	-0.017	-0.009	0.022	-0.023	0.011
	(-1.15)	(-0.65)	(1.52)	(-1.48)	(0.62)
Other Controls	Yes	Yes	Yes	Yes	Yes
Industry×Year F.E.	Yes	Yes	Yes	Yes	Yes
Adj. R^2	14.3%	7.9%	6.4%	5.8%	5.5%
Observations	33,123	28,858	24,984	21,462	18,254

Panel B: Earnings Growth

	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
H1BIntensity (t)	-0.001	0.004	0.009**	0.001	0.004
	(-0.17)	(1.17)	(2.28)	(0.15)	(1.01)
EarningsGrowth (t)	-0.231***	-0.055***	-0.030**	-0.003	-0.049***
	(-19.57)	(-4.31)	(-2.18)	(-0.19)	(-3.01)
Other Controls	Yes	Yes	Yes	Yes	Yes
Industry×Year F.E.	Yes	Yes	Yes	Yes	Yes
Adj. R^2	12.5%	3.0%	2.1%	1.8%	2.2%
Observations	33,155	28,894	25,012	21,484	18,271

Panel C: R&D Growth

	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
H1BIntensity (t)	0.041***	0.030***	0.035***	0.030***	0.033***
	(7.05)	(4.60)	(5.12)	(4.11)	(4.26)
R&DGrowth (t)	0.089***	0.000	0.014	0.012	0.025**
	(7.47)	(0.01)	(1.15)	(0.92)	(1.96)
Other Controls	Yes	Yes	Yes	Yes	Yes
Industry×Year F.E.	Yes	Yes	Yes	Yes	Yes
Adj. R^2	9.2%	4.5%	3.1%	2.7%	2.4%
Observations	33,161	28,902	25,019	21,489	18,275

Table 8: Returns Around Earnings Announcements

This table reports results of quarterly cross-sectional regressions of firms' abnormal returns around earnings announcements on past H-1B intensity. In Panel A, we use the actual announcement dates. We calculate the cumulative abnormal returns, *CAR* [-2, 1], around earnings announcement date and then sum up *CAR* of all announcements made during quarter q of fiscal year t. In Panel B, we use the "anticipated" announcement dates. We calculate *CAR* in the same week of the anticipated announcement date and then sum up *CAR* of all announcements in quarter q of fiscal year t. The dependent variable is *CAR* in quarter q of fiscal year t, and the key variable of interest is firms' H-1B intensity (*H1BIntensity*) in fiscal year $t - n$, where n equals 1 to 5. Control variables include the *ZeroH1B* indicator, market capitalization (*logMarketCap*), book-to-market ratio (*logBM*), asset growth (*AG*), operating profitability (*OperProfit*), and organization capital (*OrgCap*), all measured in fiscal year $t - n$ (the same fiscal year as H-1B petitions), as well as market beta (*Beta*), momentum (*Ret (t-12, t-2)*) and reversal (*Ret (t-36, t-13)*) variables at the previous quarter end. All non-indicator independent variables are winsorized and standardized with zero mean and unit variance. Newey-West corrected t-statistics (with 4 lags) are reported in the parentheses. The sample period is 2008/Q4 to 2020/Q4.

Panel A: Using actual announcement dates

	Dependent variable = *CAR* in quarter q of fiscal year t				
	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
H1BIntensity (t-n)	0.080***	0.116***	0.101***	0.078**	0.097***
	(3.11)	(4.24)	(3.43)	(2.29)	(3.08)
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.7%	0.6%	0.6%	0.7%	0.7%
Observations	145,970	131,219	113,060	96,233	81,125

Panel B: Using anticipated announcement dates

	Dependent variable = *CAR* in quarter q of fiscal year t				
	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
H1BIntensity (t-n)	0.026	0.055**	0.069***	0.061**	0.065**
	(1.05)	(2.02)	(2.97)	(2.10)	(2.24)
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.7%	0.7%	0.7%	0.8%	0.8%
Observations	145,903	131,160	112,998	96,217	81,095

Table 9: H-1B Intensity and Firm Fundamentals: Early versus Late Period

This table compares improvements in firms' operating performance and earnings announcement returns between the early and late periods of our sample. Specifically, we split the sample into two subperiods: an early period covering fiscal years 2008–2013 and a late period covering fiscal years 2014–2020. We examine improvement in operating performance and earnings announcement returns in early and late periods. Panel A reports results from annual panel regressions of firms' sales growth (*SalesGrowth*), earnings growth (*EarningsGrowth*), and R&D expense growth (*R&DGrowth*) in fiscal year $t{+}1$ on H-1B intensity in fiscal year t. All variable definitions and regression specifications follow those in Table 7. Panel B reports results from quarterly cross-sectional regressions of firms' abnormal returns around earnings announcements in fiscal year t on H-1B intensity in fiscal year $t-1$. All variable definitions and regression specifications follow those in Table 8. All non-indicator independent variables are winsorized and standardized with zero mean and unit variance. The sample period is 2008 to 2020 fiscal years.

Panel A: Operating performance

	SalesGrowth $(t+1)$		*EarningsGrowth* $(t+1)$		*R&DGrowth* $(t+1)$	
	Early	Late	Early	Late	Early	Late
H1BIntensity (t)	0.019***	0.017***	0.005	-0.007	0.042***	0.041***
	(3.42)	(3.49)	(1.02)	(-1.30)	(5.45)	(5.21)
SalesGrowth (t)	-0.008	-0.030				
	(-0.39)	(-1.28)				
EarningsGrowth (t)			-0.249***	-0.204***		
			(-17.10)	(-11.24)		
R&DGrowth (t)					0.085***	0.095***
					(5.34)	(5.69)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	14.8%	13.7%	13.7%	10.9%	8.8%	9.9%
Observations	18,304	14,819	18,334	14,821	18,340	14,821

Panel B: Earnings announcement returns

Dependent variable = *CAR* in quarter *q* of fiscal year *t*					
Using actual announcement dates			Using anticipated announcement dates		
	Early	Late		Early	Late
H1BIntensity $(t-1)$	0.071**	0.087**	*H1BIntensity* $(t-1)$	-0.018	0.060**
	(2.26)	(2.22)		(-0.50)	(2.07)
Controls	Yes	Yes	Controls	Yes	Yes
Adj. R^2	0.8%	0.6%	Adj. R^2	0.9%	0.7%
Observations	67,574	78,396	Observations	67,565	78,341

Table 10: Event Study Around the Presidential Election of 2016

This table reports results of an event study around the presidential election of 2016. The election occurred on November 8, 2016, which we designate as the event date (t). We measure the post-election cumulative portfolio returns (on an industry-adjusted basis) over two horizons: 3 trading days from November 8 to November 10, *CAR* (t, t+2), and 5 trading days from November 8 to November 14, *CAR* (t, t+4). To assess statistical significance, we compare the observed election-period *CAR* to an empirical distribution derived from the 180-day pre-election window. Specifically, we compute non-overlapping 3-day (5-day) cumulative (industry-adjusted) returns over the pre-election window, yielding 60 (36) historical return intervals, and compute the sample average 3-day and 5-day portfolio returns and their corresponding standard deviations. Statistical significance is assessed by measuring how many standard deviations the observed election-period *CAR* deviates from the mean of this empirical distribution. The High, Low, and Zero H-1B portfolios are constructed as in Table 3. Panel A reports the baseline results using industry-adjusted returns. Panel B presents a robustness check that additionally controls for the location effects specific to New York and California. For firms in these two states, we first regress the value-weighted average returns of all New York-based firms (and separately, all California-based firms) on industry average returns. We then subtract the residuals from these regressions, which capture location-specific returns orthogonal to industry performance, from the industry-adjusted returns of firms in each respective state.

Panel A: Industry-adjusted returns

	Pre-election 180 days: 3-day *CAR*			Post-election
H-1B Portfolio	N	Mean	Std	*CAR* (t, t+2)
High	60	0.02	0.19	-0.46**
Low	60	0.00	0.20	-0.04
Zero	60	-0.01	0.11	0.08
High–Low	60	0.02	0.30	-0.43
High–Zero	60	0.03	0.26	-0.54**
	Pre-election 180 days: 5-day *CAR*			**Post-election**
H-1B Portfolio	N	Mean	Std	*CAR* (t, t+4)
High	36	0.04	0.25	-0.73***
Low	36	0.00	0.24	-0.22
Zero	36	-0.02	0.15	0.26*
High–Low	36	0.03	0.40	-0.51
High–Zero	36	0.06	0.35	-1.00***

Panel B: Further adjusting for New York and California location effects

	Pre-election 180 days: 3-day *CAR*			Post-election
H-1B Portfolio	N	Mean	Std	*CAR* (t, t+2)
High	60	0.06	0.24	-0.64***
Low	60	0.01	0.21	-0.05
Zero	60	-0.01	0.12	0.06
High–Low	60	0.05	0.32	-0.59**
High–Zero	60	0.07	0.30	-0.69**
	Pre-election 180 days: 5-day *CAR*			**Post-election**
H-1B Portfolio	N	Mean	Std	*CAR* (t, t+4)
High	36	0.10	0.33	-1.00***
Low	36	0.01	0.25	-0.20
Zero	36	-0.01	0.14	0.26*
High–Low	36	0.09	0.45	-0.79*
High–Zero	36	0.11	0.39	-1.26***

Table 11: Determinants of H-1B Intensity

This table reports results of panel regressions of H-1B intensity on firm characteristics and headquarter city attributes during the concurrent fiscal year. In Panel A, we run probit regression using the full firm-year sample, and the dependent variable is a binary indicator of whether the firm has filed at least one H-1B petition in fiscal year *t*. In Panel B, we run panel regression using only the firm-year sample with H-1B petitions, and the dependent variable is firms' H-1B intensity (*H1BIntensity*) in fiscal year *t*. For firm characteristics, we examine market capitalization (*logMarketCap*), book-to-market ratio (*logBM*), asset growth (*AG*), operating profitability (*OperProfit*), organization capital (*OrgCap*), and R&D capital (*RDC*). For city attributes, *ImmigrantOffice* is an indicator that equals one if the firm's headquarter city has established an immigrant integration office in the current year, and zero otherwise; *AsianRatio* is the percentage of Asians over total population; *CityBM* and *CityRDC* are city-level average book-to-market ratio and R&D capital (both adjusted by industry average). All non-indicator independent variables are winsorized and standardized with zero mean and unit variance. We add year fixed effects, industry fixed effects, and industry$\times$year fixed effects, respectively, and cluster standard errors by firm. The sample period is 2008 to 2020 fiscal years.

	Panel A: Probit regression Dependent variable = *H1B (0 or 1)* (Full sample)			Panel B: Panel regression Dependent variable = *H1BIntensity* (Subsample of H-1B petitions >= 1)		
	(1)	(2)	(3)	(4)	(5)	(6)
logMarketCap	0.467***	0.512***	0.522***	0.011	0.113**	0.115**
	(20.13)	(19.52)	(19.60)	(0.23)	(2.56)	(2.49)
logBM	0.025	0.083***	0.082***	-0.151***	-0.091**	-0.088**
	(1.32)	(4.01)	(3.86)	(-4.00)	(-2.50)	(-2.30)
AG	-0.008	-0.016*	-0.017*	0.106***	0.068***	0.069***
	(-0.98)	(-1.70)	(-1.80)	(6.78)	(4.51)	(4.43)
OperProfit	0.080***	0.043**	0.043**	-0.045	-0.051*	-0.040
	(5.18)	(2.51)	(2.48)	(-1.45)	(-1.72)	(-1.34)
OrgCap	0.246***	0.160***	0.165***	0.009	0.055	0.052
	(13.34)	(6.66)	(6.78)	(0.23)	(1.19)	(1.08)
RDC	0.109***	0.068***	0.067***	0.215***	0.117***	0.117***
	(6.08)	(3.11)	(3.02)	(5.24)	(2.86)	(2.76)
ImmigrantOffice	0.085**	0.077**	0.086**	0.088	0.101*	0.100
	(2.38)	(2.01)	(2.22)	(1.30)	(1.66)	(1.56)
AsianRatio	0.128***	0.118***	0.119***	0.303***	0.195***	0.196***
	(5.70)	(4.45)	(4.47)	(7.94)	(5.12)	(5.01)
CityBM	-0.024	-0.024	-0.027	0.024	0.009	0.011
	(-1.30)	(-1.27)	(-1.42)	(0.65)	(0.27)	(0.30)
CityRDC	0.090***	0.028	0.023	0.204***	0.118***	0.119***
	(3.98)	(1.10)	(0.91)	(4.36)	(2.67)	(2.59)
Year F.E.	Yes	Yes	No	Yes	Yes	No
Industry F.E.	No	Yes	No	No	Yes	No
Industry$\times$Year F.E.	No	No	Yes	No	No	Yes
Adj. R^2				21.2%	38.5%	37.3%
Observations	35,234	32,431	32,316	10,977	10,157	10,105

Table 12: H-1B Intensity Decomposition

This table reports results of monthly cross-sectional regressions of stock returns on the expected and residual components of H-1B intensity. At the end of each fiscal year *t*, we run a cross-sectional regression based on Equation (1) to decompose firms' H-1B intensity, using the firm-year sample with at least one H-1B petition in fiscal year *t*. All variables are from the same fiscal year *t* and we use beta estimates in the concurrent year to decompose *H1BIntensity* into the expected and residual components. *ExpectedH1BFirm* is the expected component based on firm and industry attributes, which is the predicted value using the intercept, *logMarketCap*, *logBM*, *AG*, *OperProfit*, *OrgCap*, *RDC*, and industry fixed effects (using Fama-French 49-industry classifications). *ExpectedH1BCity* is the expected component based on headquarter city attributes, which is the predicted value using *ImmigrantOffice*, *AsianRatio*, *CityBM*, and *CityRDC*. The residual component, *ResidualH1B*, is the difference between the actual *H1BIntensity* and the sum of the two expected components. We then run Fama-MacBeth cross-sectional regressions of monthly stock returns on the residual and expected components of *H1BIntensity*. The dependent variable is monthly stock returns (in excess of the risk-free rate) in fiscal year *t*. The main variables of interest are the expected and residual components of *H1BIntensity* in fiscal year *t–n*, where *n* equals 1 to 5. All independent variables are winsorized and standardized with zero mean and unit variance. Newey-West corrected *t*-statistics (with 12 lags) are reported in the parentheses. The sample period is 2008/10 to 2020/12.

	Dependent variable = Monthly returns in fiscal year *t*				
	n = 1	*n* = 2	*n* = 3	*n* = 4	*n* = 5
ResidualH1B (t-n)	0.092**	0.091**	0.110**	0.081	0.138*
	(2.22)	(2.42)	(2.08)	(1.27)	(1.89)
ExpectedH1BFirm (t-n)	0.103	0.095	0.074	0.090	0.128*
	(1.52)	(1.33)	(0.97)	(1.21)	(1.68)
ExpectedH1BCity (t-n)	0.141***	0.089*	0.092**	0.111**	0.135***
	(2.62)	(1.78)	(2.28)	(2.38)	(2.80)
Beta	0.046	-0.062	-0.068	-0.004	-0.032
	(0.21)	(-0.38)	(-0.39)	(-0.02)	(-0.16)
Ret (t-12, t-2)	-0.204	-0.039	0.098	-0.153	-0.113
	(-1.00)	(-0.45)	(1.02)	(-1.32)	(-0.76)
Ret (t-36, t-13)	0.093	0.180	0.232	0.209	0.130
	(0.59)	(1.47)	(1.45)	(1.43)	(0.68)
Adj. R^2	4.0%	3.4%	3.5%	3.7%	4.0%
Observations	109,232	97,745	85,288	73,630	62,816

Table 13: Differential Impact of H-1B Intensity Across Cities

This table repeats the Fama-MacBeth regressions in Table 4 while controlling for aggregate H-1B intensity around a firm's headquarter location. *H1BIntensityCity* is the logarithm of aggregate H-1B petitions over aggregate employees ratio in the core-based statistical area (CBSA) where a firm's headquarter locates. We also include the interaction term between firm-level and city-level H-1B intensity measures, *H1BIntensity×H1BIntensityCity*. Low-, Mid- and High-H1B Cities are defined using the 33^{rd} and 67^{th} percentile of the distribution of *H1BIntensityCity*. Control variables are the same as in Table 4. All non-indicator independent variables are winsorized and standardized with zero mean and unit variance. Newey-West corrected t-statistics (with 12 lags) are reported in the parentheses. The sample period is 2008/10 to 2020/12.

Panel A: Forecasting returns in the next year

	Dependent variable = Monthly returns in fiscal year t			
	Low-H1B Cities	Mid-H1B Cities	High-H1B Cities	All Cities
H1BIntensity (t-1)	0.011	0.055	0.117***	0.054***
	(0.18)	(1.29)	(2.85)	(2.74)
H1BIntensityCity (t-1)				0.012
				(0.56)
H1BIntensity×H1BIntensityCity (t-1)				0.066**
				(2.48)
Controls	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	13.0%	9.9%	5.8%	7.0%
Observations	79,121	112,825	209,093	415,230

Panel B: Forecasting returns in the subsequent 2 to 5 years

	Dependent variable = Monthly returns in fiscal year t			
	$n = 2$	$n = 3$	$n = 4$	$n = 5$
H1BIntensity (t-n)	0.055**	0.049	0.029	0.055
	(2.20)	(1.63)	(1.14)	(1.57)
H1BIntensityCity (t-n)	0.016	0.021	0.021	0.014
	(0.81)	(0.95)	(0.90)	(0.68)
H1BIntensity×H1BIntensityCity (t-n)	0.043**	0.040**	0.051***	0.058***
	(2.09)	(2.23)	(2.73)	(2.76)
Controls	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	6.7%	6.9%	7.0%	7.2%
Observations	371,633	322,956	277,898	236,596

Appendix A Variable Definitions

Book-to-Market Ratio (*BM*)

BM is defined as the book equity for the fiscal year ending in year t divided by the market equity at the end of December of t. Following Davis, Fama, and French (2000), book equity is shareholders' equity, plus balance sheet deferred taxes and investment tax credit (Compustat item TXDITC) if available, minus the book value of preferred stocks. Shareholders' equity is Compustat item SEQ if available, or the book value of common equity (CEQ) plus the carrying value of preferred stocks (PSTK), or total assets (AT) minus total liabilities (LT), depending on data availability. Book value of preferred stocks is the redemption value (PSTKRV), or the liquidating value (PSTKL), or the carrying value of preferred stocks (PSTK), depending on availability.

Operating Profitability (*OperProfit*)

Following Fama and French (2015), *OperProfit* is defined as annual revenues (Compustat item REVT) minus cost of goods sold (COGS), interest expense (TIE), and selling, general, and administrative expenses (XSGA) divided by book equity. Following Davis, Fama, and French (2000), book equity is shareholders' equity, plus balance sheet deferred taxes and investment tax credit (TXDITC) if available, minus the book value of preferred stocks. Shareholders' equity is Compustat item SEQ if available, or the book value of common equity (CEQ) plus the carrying value of preferred stocks (PSTK), or total assets (AT) minus total liabilities (LT), depending on data availability. Book value of preferred stocks is the redemption value (PSTKRV), or the liquidating value (PSTKL), or the carrying value of preferred stocks (PSTK), depending on availability.

Cash-based Operating Profitability (*CbOP*)

Cash-based operating profitability (*CbOP*) is defined following Ball, Gerakos, Linnainmaa, and Nikolaev (2016). Operating profitability is measured as revenue (REVT) minus cost of goods sold (COGS) minus reported sales, general, and administrative expenses (XSGA$-$XRD (zero if missing)). Prior to 1988, we use the balance sheet statement and measure *CbOP* as operating profitability minus the change in accounts receivable (RECT) minus the change in inventory (INVT) minus the change in prepaid expenses (XPP) plus the change in deferred revenues (DRC+DRLT) plus the change in accounts payable (AP) plus the change in accrued expenses (XACC), deflated by current total assets. Starting from 1988, we use the cash flow statement and measure *CbOP* as operating profitability plus decrease in accounts receivable ($-$RECCH) plus decrease in inventory ($-$INVCH) plus increase in accounts payable and accrued liabilities (APALCH), deflated by current total assets.

Asset Growth (*AG*)

Following Cooper, Gulen, and Schill (2008), asset growth is defined as the growth in total assets (Compustat item AT) scaled by beginning total assets. For each firm i in year t,

$$AG_{it} = \frac{AT_{it} - AT_{it-1}}{AT_{it-1}};$$

Organization Capital (*OrgCap*)

Following Eisfeldt and Papanikolaou (2013), *OrgCap* is measured using the perpetual inventory method. For each firm i in year t,

$$OrgCap_{it} = (1-\delta)OrgCap_{it-1} + SG\&A_{it}/CPI_t,$$

where SG&A is selling, general, and administrative expenses (Compustat item XSGA), CPI is the consumer price index during year t, and δ is the annual depreciation rate. We closely follow Green, Hand, and Zhang (2017) for detailed definition of each variable, and then scale $OrgCap_{it}$ by the average of beginning and ending total assets (AT).

R&D Capital (*RDC*)

Following Chan, Lakonishok, and Sougiannis (2001), we estimate the stock of R&D capital from the past history of R&D expenditures (Compustat item XRD). RDC_{it} for firm i in year t is based on current and past R&D expenditures, scaled by the average of beginning and ending total assets (AT).

$$RDC_{it} = \frac{XRD_{it} + 0.8 * XRD_{it-1} + 0.6 * XRD_{it-2} + 0.4 * XRD_{it-3} + 0.2 * RD_{it-4}}{(AT_{it} + AT_{it-1})/2}$$

Sales Growth (*SalesGrowth*)

SalesGrowth is the natural logarithm of the growth in sales (Compustat item SALE). For each firm i in year t,

$$SalesGrowth_{it} = ln(SALE_{it} + 1) - ln(SALE_{it-1} + 1)$$

Earnings Growth (*EarningsGrowth*)

EarningsGrowth is the growth in net income (Compustat item NI) scaled by beginning total asset (AT). For each firm i in year t,

$$EarningsGrowth_{it} = \frac{NI_{it} - NI_{it-1}}{AT_{it-1}};$$

R&D Growth (*R&DGrowth*)

R&DGrowth is the natural logarithm of the growth in R&D expenditures (Compustat item XRD). For each firm i in year t,

$$R\&DGrowth_{it} = ln(XRD_{it} + 1) - ln(XRD_{it-1} + 1)$$

Internet Appendix

Table A.1: Alternative Measures of H-1B Intensity

This table reports the pairwise correlation between our main measure of firm H-1B intensity and a set of alternative measures. Our main measure, *H1BIntensity*, is constructed based on the total number of LCA petitions a firm has filed during a fiscal year. We construct alternative measures utilizing a set of additional data fields available starting in 2018, including the total worker positions being requested for each LCA petition and reasons for the petition (new employment, renewals for current employment, change of employer, amendments to existing employment based on changes in job description, etc.). Specifically, *Alt.H1BIntensity (total worker positions)* is created based on the sum of total worker positions (data field "TOTAL_WORKER_POSITIONS") requested in all LCAs a firm has filed during a fiscal year. *Alt.H1BIntensity (non-amended positions only)* is based on the sum of total worker positions excluding amended positions (data field "AMENDED_PETITION"). *Alt.H1BIntensity (new employment only)* is created using only new employment positions (data field "NEW_EMPLOYMENT"). *Alt.H1BIntensity (continued employment only)* is created using only continued employment positions (data fields "CONTINUED_EMPLOYMENT" and "CHANGE_PREVIOUS_EMPLOYMENT"). *Alt.H1BIntensity (change of employer only)* is created using change-of-employer positions (data fields "CHANGE_EMPLOYER" and "NEW_CONCURRENT_EMPLOYMENT") only. All measures are scaled by the firm's total labor force in the prior year. The alternative measures are available after 2018.

Fiscal Year	Alternative Measures	*H1BIntensity* *(Total number of LCAs)*
2018	*Alt.H1BIntensity (total worker positions)*	0.96
2018	*Alt.H1BIntensity (non-amended positions only)*	0.96
2018	*Alt.H1BIntensity (new employment only)*	0.89
2018	*Alt.H1BIntensity (continued employment only)*	0.87
2018	*Alt.H1BIntensity (change of employer only)*	0.85
2019	*Alt.H1BIntensity (total worker positions)*	0.96
2019	*Alt.H1BIntensity (non-amended positions only)*	0.95
2019	*Alt.H1BIntensity (new employment only)*	0.89
2019	*Alt.H1BIntensity (continued employment only)*	0.87
2019	*Alt.H1BIntensity (change of employer only)*	0.83
2020	*Alt.H1BIntensity (total worker positions)*	0.96
2020	*Alt.H1BIntensity (non-amended positions only)*	0.96
2020	*Alt.H1BIntensity (new employment only)*	0.88
2020	*Alt.H1BIntensity (continued employment only)*	0.89
2020	*Alt.H1BIntensity (change of employer only)*	0.83

Table A.2: Returns of H-1B Intensity Portfolios: Excluding the Largest Firms

This table presents robustness checks for the portfolio return results reported in Table 3. We follow the same portfolio formation methodology, but exclude the largest firms with market capitalization above the 90^{th} percentile of NYSE size breakpoints.

Panel A: Annualized (industry-adjusted) portfolio returns (%) over 5-year horizon

Portfolios	N firms	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Zero	2651.5	0.43	0.46	0.21	-0.06	-0.40
		(0.57)	(0.62)	(0.23)	(-0.06)	(-0.28)
Low	177.7	1.17	0.62	0.52	0.36	-0.01
		(1.71)	(0.60)	(0.44)	(0.30)	(-0.01)
2	187.2	-0.75	-0.18	-1.57	-0.21	-0.44
		(-0.76)	(-0.19)	(-1.08)	(-0.19)	(-0.33)
3	182.6	1.43	-1.36	-0.53	0.52	-0.13
		(1.07)	(-1.03)	(-0.41)	(0.33)	(-0.06)
4	180.9	0.11	3.05	1.65	-0.37	-0.28
		(0.06)	(2.16)	(1.12)	(-0.20)	(-0.17)
High	171.9	3.57	2.16	1.49	2.60	3.33
		(2.93)	(2.41)	(1.89)	(2.51)	(2.24)
High–Low		2.40*	1.54	0.97	2.23*	3.34**
		(1.86)	(1.26)	(0.82)	(1.87)	(2.54)
High–Zero		3.15**	1.70**	1.28	2.66**	3.73***
		(2.61)	(2.22)	(1.43)	(2.85)	(4.36)

Panel B: Annualized (industry-adjusted) portfolio returns and alphas (%) over 1-year horizon

	Zero	Low	2	3	4	High	High–Low	High–Zero
Average return	0.36	0.84	-0.84	1.44	0.00	3.84	3.00	3.48**
	(0.33)	(0.65)	(-0.75)	(1.05)	(-0.01)	(1.80)	(1.48)	(2.01)
CAPM alpha	-1.08	-1.08	-2.64	0.24	-2.28	2.16	3.24	3.24*
	(-1.19)	(-0.97)	(-2.60)	(0.15)	(-1.27)	(0.99)	(1.42)	(1.68)
FF5 alpha	-0.36	0.24	-1.32	1.44	-0.36	3.12	2.88	3.48**
	(-0.71)	(0.28)	(-1.54)	(1.36)	(-0.32)	(1.80)	(1.65)	(2.01)
FF6 alpha	-0.36	0.24	-1.44	1.44	-0.60	2.88	2.76	3.24**
	(-0.72)	(0.19)	(-1.66)	(1.33)	(-0.43)	(1.76)	(1.61)	(2.01)
$q5$ alpha	0.72	0.24	-0.48	1.92	-0.12	4.32	4.08*	3.60**
	(1.08)	(0.25)	(-0.49)	(1.59)	(-0.08)	(2.32)	(1.93)	(2.04)
DHS alpha	-0.24	-0.72	-2.16	1.20	-0.84	3.48	4.20**	3.72**
	(-0.25)	(-0.60)	(-2.18)	(0.92)	(-0.52)	(1.84)	(2.47)	(2.37)

Table A.3: Returns Around Earnings Announcements for Firms in the Top H-1B Quintile

This table replicates the analysis in Table 8, replacing the main explanatory variable with an indicator, *High_H1BIntensity*, that equals one if a firm is in the top quintile of H-1B intensity in fiscal year $t-n$ (where n ranges from 1 to 5), and zero otherwise. In Panel A, we use the actual announcement dates. We calculate the cumulative abnormal returns, *CAR* [-2, 1], around earnings announcement date and then sum up *CAR* of all announcements made during quarter q of fiscal year t. In Panel B, we use the "anticipated" announcement dates. We calculate *CAR* in the same week of the anticipated announcement date and then sum up *CAR* of all announcements in quarter q of fiscal year t. The dependent variable is *CAR* in quarter q of fiscal year t. Control variables are the same as Table 8. Newey-West corrected t-statistics (with 4 lags) are reported in the parentheses. The sample period is 2008/Q4 to 2020/Q4.

Panel A: Using actual announcement dates

	Dependent variable = *CAR* in quarter q of fiscal year t				
	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
High_H1BIntensity (t-n)	0.498***	0.570***	0.730***	0.714***	0.723***
	(3.90)	(4.17)	(4.93)	(3.58)	(3.67)
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.7%	0.6%	0.6%	0.7%	0.7%
Observations	145,970	131,219	113,060	96,233	81,125

Panel B: Using anticipated announcement dates

	Dependent variable = *CAR* in quarter q of fiscal year t				
	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
High_H1BIntensity (t-n)	0.315**	0.495***	0.599***	0.526***	0.596***
	(2.63)	(3.84)	(4.30)	(3.42)	(4.02)
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.8%	0.7%	0.7%	0.8%	0.8%
Observations	145,906	131,159	112,998	96,217	81,095