EXHIBIT 14

Skilled Foreign Labor, Urban Agglomeration, and Value Creation

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Abstract

Firms employing more H-1B visa holders have higher market-to-book values than their industry peers and realize excess *future* stock returns, particularly on earnings announcement dates, suggesting that the market initially underreacts to the value created. The returns are higher in talent clusters: doubling the number of H-1B workers in a city doubles the sensitivity between a firm's own H-1B hiring and 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.

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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

Over four decades ago in "The Economic of Superstars (1981)," Rosen explored why, in many markets, the financial rewards at the right tails of the talent distribution were so high. Comedians, violinists, and academics are offered as examples where mere competence offers a livelihood, but excellence provides the prospect of fortune or even fame. Critically, what generates the concentration of financial rewards is not the distribution of talent itself, but rather its amplification via technology. Although Rosen could not have foreseen the speed and totality with which information technology would come to dominate nearly every industry, the contemporary relevance of his insights is revealed through the quotes above. In an era where ideas matter more than machines, the creators of those ideas – talent – ultimately matter the most.

Although the importance of talent is widely acknowledged, the extent to which firms extract the associated surplus is unclear. In a perfectly competitive market, individuals with special skills should capture the benefits. However, because of the scarcity of complementary technologies, synergies between individuals, and moving and search costs, firms may have monopsony power allowing them to capture some of the benefits of a talented workforce. Such rents fall under the broad umbrella of *organization capital*, as described originally by Prescott and Visscher (1980).

The sentiment in the quotes above is both typical and ubiquitous in the financial press, suggesting a near-universal perception among top executives that a firm's workforce is a critical factor in its ability to create shareholder value. Hence, it is perhaps surprising that with few exceptions, there is not much empirical work that explicitly links proxies for the productivity of a firm's workers to the financial rewards enjoyed by the firm's owners. This paper attempts to fill this gap, using data on H-1B visas, which are awarded to foreign-born workers with specialized skills, in partnership with U.S. employers as sponsors.

There are two main empirical obstacles we seek to overcome. The first issue relates to measurement. Trivially, better and/or more skilled workers are more productive, but this does not necessarily translate to superior financial performance. Some of the surplus will be captured by workers through higher wages, some by land owners through higher rents (Hornbeck and Moretti, 2024), and some by customers through price competition. To focus on the benefits received by the firm's owners, we will focus on variables like market-to-book ratios and particularly stock returns, along with various measures of accounting performance that are downstream of wages, rent/land costs, and pricing.

The second issue is omitted variable bias, arising because the value derived from a firm's workforce is likely to complement other source of value (e.g., its technology). We illustrate this with a simple model involving two sources of comparative advantage. First, firms may create value through their assets, either tangible or intangible. This is modeled through a TFP parameter A, and abstracts from the numerous ways firms may differ in terms of plant efficiency, brands, patents, and so on. The second factor, α, captures the firm's ability to extract rents from workers. The identification problem arises because in equilibrium, firms with better assets (high A) also hire more talented workers (high α). Hence, to isolate the effect of α on firm performance, the econometrician must effectively hold A constant.

To better appreciate the issue, consider a cross-sectional regression of market-to-book ratios on the fraction of a firm's workers that hold H-1B visas, a proxy for highly skilled foreign born workers. This reveals a strong, positive association, with the top quintile of H-1B hiring firms having valuation ratios roughly 50% higher than their industry peers with fewer H-1B workers. An abiding concern, however, is that these are simply different types of firms in terms of their fundamentals, and that sector, geographic, and firm-level controls fail to soak up the unobserved heterogeneity.

Accordingly, our empirical strategy takes a different route. Rather than attempt to explicitly control for differences in firms' assets, we combine time-series tests with assumptions about how the information environment evolved over the relevant horizon.

More specifically, we assume that as the IT revolution unfolded, 1) the associated value created from a firm's assets (A in the model) was well understood and quickly reflected in securities prices, but that 2) stock markets may have underestimated the role skilled workers would play in value creation (α), leading to sluggish price reactions.

Why do we regard this as a plausible assumption? Thomas Friedman's wildly successful 2005 bestseller "The World Is Flat" perhaps best captured the zeitgeist at the time, predicting that new technologies would free firms from the shackles of local labor and consumer markets, giving rise to the eponymous flattening of the global business landscape. While Friedman's predictions about the offshoring of manufacturing were quickly vindicated, his critics pointed out that the production of ideas — activities involving creativity, research, and design — became *more* concentrated since the book's publication, giving rise to "spiky" contours in innovation. Only a few years later, Moretti's (2013) "The New Geography of Jobs" relied on Marshallian externalities to microfound emerging productivity powerhouses like the San Francisco Bay Area, Seattle, and then-fledging Austin, TX. What made these locations so special, Moretti argues, is both the skill and ability of individual workers, and critically, the local ecosystems that allows ideas to flow both within and across firms.

Standing in the mid-to-late 2000s, it thus seems difficult to believe that stock markets failed to understand the emerging impact of globalization for consumer markets, or how IT and lower shipping costs would alter manufacturing locations. On the other hand, how these forces would act as fulcrums, off of which a firm's talent base could leverage their capabilities, was far less obvious. If the latter had been understood by markets, proxies for a firm's skilled labor would have been associated with high valuations, but not high stock returns (i.e., changes in valuations) over the ensuing years. On the other hand, if the market was gradually learning about the importance of skilled labor for value – potentially as a complement to the accompanying technology shocks – we would expect to find evidence in their return histories.

Our proxy for a firm's access or ability to attract the type of skilled labor most important for value creation is the usage of H-1B visas. Although the program's founding goes back to 1990, throughout the 1990s and much of the 2000s, the program was sparsely used, seldom reaching the annual quota, and attracting almost no attention by the general or financial media.[1] Only starting from 2006 did firm demand for H-1B workers begin to regularly exceed supply, when a lottery system was implemented (see, e.g., Doran, Gelber, and Isen, 2022). Hence, from around this time, we hypothesize that significant value was already being created. The question is whether, and to what extent, this was recognized by the stock market.

Our first set of results, presented in Section 5, suggests a sluggish reaction. When firms are sorted by H-1B visa applications, there is an increasing relation with future industry-benchmarked returns. The relation is non-linear, with the top quintile outperforming the other groups by about 40 basis points per month, between which there is little effect. Standard risk adjustments make almost no difference, with alphas being nearly identical to the differences in raw returns between H-1B sorted portfolios. Nor are the excess returns solely attributable to a few large firms employing large numbers of H-1B workers. For example, excluding the top 10% of the size distribution still generates yearly alphas of 4-5% for the highest H-1B firms.

One way to appreciate these magnitudes is to estimate the dollars of value created for shareholders implied by the excess returns. In 2008, the total market capitalization of the highest H-1B quintile was about $1.1 trillion. If one continually reinvested in the 20% of firms hiring the most H-1B workers (which might be different firms over time), the portfolio grows to over $11.2 trillion by the end of 2020.[2] An alternative calculation would take the realized returns of this portfolio every month, and subtract 40 bps, which is the Fama-French-6-factor alpha over this time period. Here, one would arrive at a terminal value of only $6.3 trillion, roughly $5 trillion less than what shareholders actually received. With the normal limitations of factor models acknowledged, this implies enormous value creation for shareholders, and would have accounted for about 15% of the total stock market capitalization in 2020.

Revisiting the return patterns, although standard risk adjustments don't explain much of the superior stock performance of high H-1B firms, a concern is whether these firms are, in fact, riskier. Two additional pieces of evidence point to higher expected cash flows, which

[1]The annual quota or cap for H-1B visas was initially set at 65,000 by the Immigration Act of 1990. It was increased to 115,000 for fiscal years 1999 and 2000, then further raised to 195,000 for the years 2001 to 2003. In 2004, the cap reverted back to 65,000.

[2]According to Panel A of Figure 3, every $1 investment in the top H-1B quintile portfolio in October 2008 grew to $10.4 by December 2020, yielding an average realized return of 1.6% per month.

are incorporated into prices with a delay. First, multiple measures of firm fundamentals are predictable from lagged H-1B hiring, in particular growth in sales, earnings, and R&D. Second, returns around earnings announcements display an especially strong effect: H-1B hiring positively forecasts cumulative abnormal returns ($CARs$) during weeks with either actual or anticipated earnings announcements, and accounts for roughly half the estimated yearly alpha.

The second part of the paper uses geography to hopefully sharpen a causal interpretation running from skilled labor to firm values. 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), our identifying assumption in this section is that there exist observable characteristics of these cities that make them particularly attractive to foreign-born workers. Critically, we further assume that these characteristics are orthogonal to A, capturing the contribution of firm value that is related to the firm assets rather than skilled workers.

One characteristic is whether a city is home to an "Immigrant Integration Office," which provides a number of useful services for foreign-born residents.[3] 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. These city-level proxies do in fact strongly predict H-1B hiring, but are relatively static, and hence, should not reflect ebbs and flows of resident firms' prospects.

Our analysis in Section 6 uses these city specific variables along with firm-specific variables as explanatory variables in a regression that predicts the relative proportions of H-1B visa holders hired by each firm. As we show, firm-specific variables, like R&D expenditures, as well as city-specific variables, like the percentage of Asians in a city, predict the magnitude of H-1B hiring. Based on this analysis, we decompose the magnitude of H-1B hiring into a component that can be explained by: 1) firm-specific attributes, 2) city-specific attributes, 3) the residual. The results from this exercise provide further evidence of causation.

Predicted H-1B hiring from city-level characteristics forecasts future stock returns. In

[3]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.

contrast, predicted H-1B hiring from firm characteristics (e.g., size, book-to-market, asset growth, operating profits, R&D expenditures, etc.) is not reliably related to future returns. However, H-1B hiring that cannot be explained by *either* firm or city attributes (i.e., the residual component) does explain future stock returns.

To 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. Here, the idea is that foreign talent may work more effectively in communities with an existing concentration of other foreign-born workers, and that some of these positive spillovers are captured by shareholders. To test this hypothesis, we include a term that interacts the intensity of a firm's H-1B hiring with a measure of the H-1B intensity of the host city. We find that the effect on a firm's future returns from H-1B hiring roughly doubles with every standard deviation of city-level H-1B hiring. The increasing marginal benefit of talent in cities that attract more skilled foreign labor is consistent with synergies that may arise through local knowledge spillovers, or simply because these cities attract the best talent. In either case, the result illustrates the value associated with locating in these talent hubs.

Our final evidence in Section 7 comes from an event study made possible by the U.S. Presidential election in 2016. Then-candidate Donald Trump 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. Because the outcome of the election was a surprise, this represents a sharp, heterogeneous shock to firms with better access to future H-1B employees. Indeed, when we make this comparison, we find that firms hiring more H-1B workers experienced a near-immediate value decline of roughly 2% in the few days surrounding the election, compared to firms with little or no H-1B employees. These findings are robust to controls for both industry and firms' headquarter locations.

Our paper contributes to the growing literature on how labor force dynamics influence asset prices and corporate behavior. Prior studies show that labor mobility and hiring adjustment costs negatively affect firm value (e.g., 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, while 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 organizational capital.[4] While these studies primarily approach the link between talent and stock returns from a discount rate perspective, this paper investigates the impact on cash flows, and the market's ability to recognize the effects in a timely manner.

In this way, our paper is related to Agrawal, Hacamo, and Hu (2021) which, using LinkedIn data to measure firm-level flows of rank-and-file workers, documents near-term predictability in both stock returns and fundamentals. In that paper, the authors interpret ebbs and flows of workers at time t as signals about innovations in firms' future general prospects (A_{t+1} in our simple model). The hope of our empirical approach is to complement this mechanism and identify a *causal* channel for (some types of) workers on firm values, beyond their values as informative signals. In this way, the city-level analysis plays a particularly important role, as does the 2016 election result, both of which more precisely focus on H-1B workers specifically, and their relation to firm values.

We also contribute to the literature on foreign immigrant labor, particularly H-1B visa holders. Prior studies explore how H-1B hiring influences innovation and labor productivity, with some suggesting 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).[5] Recent studies find that access to high-skilled foreign labor is crucial for start-up success (Chen, Hshieh, and Zhang, 2021; Dimmock, Huang, and Weisbenner, 2022). Additionally, studies show that restrictions on hiring skilled foreign workers reduce investment (Xu, 2022), increase offshoring by U.S. multinationals (Glennon, 2020), and drive "acqui-hiring" through mergers and acquisitions (Chen, Hshieh, and Zhang, 2023). While these studies primarily focus on the impact of H-1B workers on firm innovation activities and other corporate decisions, our paper extends this literature by demonstrating that H-1B hiring increases shareholder value and establishing a causal link between their employment and firm value creation.

Another related strand of literature examines the link between firm headquarters

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

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

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 high 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.

2 Talent and Firms: A Simple Framework

To motivate our empirical analysis, we start with a simple theory linking the talent of a firm's workforce to its hiring choices and profits. The output of firm i is

$$Y_i = A_i L_i^{\alpha_{i,city}}, \tag{1}$$

where L_i refers to the firm's choice of skilled foreign-born (H-1B) talent. Parameter A_i, the firm's total factor productivity, encapsulates the impact of its *assets*, both tangible and intangible. Examples might be plant or production efficiency, brands, patents, or other technology that leads to differential output. The i subscript indicates that these asset-specific sources of value creation are assumed to vary in the cross-section of firms. The second parameter captures a firm's ability to extract value from its skilled labor. We model this exploitation of a firm's *talent* through a decreasing returns to scale parameter $\alpha_{i,city} < 1$. The two subscripts shown are intended to capture the idea that α may vary in the cross-section of firms (i), and in addition, may be higher in some cities than in others ($city$).

Normalizing both the price of the firm's output and wage (per-unit L) to one, dropping subscripts, and solving the firm's F.O.C. for L gives

$$L^* = \left(\frac{1}{A\alpha}\right)^{\frac{1}{\alpha-1}}, \tag{2}$$

and profits π^*, or revenues (Y^*) minus wage costs (L^*), of

$$\pi^* = (A\alpha)^{\frac{1}{1-\alpha}} \left(\frac{1-\alpha}{\alpha}\right). \tag{3}$$

Equations 2 and 3 jointly provide the foundation for our empirical analysis.

Proposition 1. *For $L^* > 1$, which guarantees that profits increase with α, higher labor productivity (α) increases a firm's demand for workers, $\frac{\partial L^*}{\partial \alpha} > 0$, and increases its profits, $\frac{\partial \pi^*}{\partial \alpha} > 0$.*

Proof. From Eq. (2), $A > \frac{1}{\alpha} \implies L^* > 1$. $\frac{\partial L^*}{\partial \alpha} = \dfrac{\left(\frac{1}{A\alpha}\right)^{\frac{1}{1-\alpha}} \left(\left(\ln\left(\frac{1}{A\alpha}\right)+1\right)\alpha - 1\right)}{(\alpha-1)^2\alpha}$, which is positive if $A > \frac{e^{\frac{\alpha-1}{\alpha}}}{\alpha}$, which is implied by $A > \frac{1}{\alpha}$. For the firm's profits, $\frac{\partial \pi^*}{\partial \alpha} = \dfrac{(A\alpha)^{\frac{1}{1-\alpha}} \ln(A\alpha)}{(1-\alpha)\alpha}$, which is positive if $A > \frac{1}{\alpha}$. □

The above proposition is the focus of our empirical analysis. Specifically, it highlights one channel through which firms can create value. When workers do not fully capture their marginal product via wages, firms extract the residual as a rent. Note that we model this effect in a particularly simple way, with wages being flat. However, the more general intuition is straightforward: wages will be determined by the least efficient firm still making positive profits ($\bar{\alpha}$), allowing all firms with $\alpha > \bar{\alpha}$ to obtain rents. We refer to this first channel of value creation as being *talent driven,* similar to Eisfeldt and Papanikolaou (2013), which stresses organizational capital as being embodied in the firm's "top talent."

Proposition 1 thus provides one reason why an increase in H-1B workers might be positively correlated with the firm's value or operating performance. If firms and markets are equally well-informed about labor productivity α, increases in L may forecast changes in operating performance, but will not generate return predictability. However, if the stock market fails to sufficiently update current or future productivity (α) from hiring choices, L may lead to predictable stock returns as well as operating performance.

The following proposition describes a second channel through which firms can create value, and hence, constitutes the key identification channel we hope to overcome in our empirical tests.

Proposition 2. *An increase in A increases resident firms demand for H-1B workers, $\frac{\partial L^*}{\partial A} > 0$, and increases its profits, $\frac{\partial \pi^*}{\partial A} > 0$.*

Proof. $\frac{\partial \pi^*}{\partial A} = \dfrac{(A\alpha)^{\frac{1}{1-\alpha}}}{A\alpha} > 0$, given $A > 0$ and $\alpha > 0$. $\frac{\partial L^*}{\partial A} = \dfrac{\left(\frac{1}{A\alpha}\right)^{\frac{1}{\alpha-1}}}{A\,(1-\alpha)} > 0$ following from $\alpha < 1$. □

Firms with superior capabilities or opportunities, captured by TFP parameter A, are expected to invest at higher rates – including hiring more workers – and enjoy higher profits and firm values. As with α, A might, in practice, be difficult for the market to perfectly observe. Moreover, failing to fully back out A from L may generate a lead-lag relation between a firm's hiring choices (L), and its future financial and/or operating performance (π or capitalized variables like stock prices).

The two propositions above help us motivate and interpret the empirical tests that follow. The first proposition shows that firms with greater α, which captures the talent-based contribution to value, hire more skilled labor and also have higher firm values. Hence, if fluctuations in α are the only source of variation in the employment of skilled labor, then an observed positive relationship between changes in skilled labor and stock returns is an indicator of the importance of talent-based value. The second proposition illustrates the identification challenge. It shows that there is an additional source of variation in a firm's hiring choices, which is related to the productivity of the firm's physical capital and technology. This channel can generate a positive, though spurious, correlation between the hiring of skilled labor and firm values even when workers capture all the talent-based surplus.

The distinction between the roles played by the TFP parameter (A) and the exponent on labor productivity (α) is worth noting. Higher values of both parameters increase the firm's output and profits and heterogeneity in firm values when capitalized. In this sense, both correspond to sources of comparative advantage, and hence, can be conceptualized as capturing different aspects of value creation. While all sources of value creation can be modeled through a generic TFP parameter, which may vary across either firms (Atkeson and Kehoe, 2005) or space (Hornbeck and Moretti, 2024), we isolate the labor-based contribution with its own parameter (α), to provide clear empirical guidance for the tests that follow.

To empirically distinguish between value creation arising from a firm's talent base versus value created because of superior assets, we rely on two assumptions. The first is that although the H-1B program was not new, it became increasingly important during our sample period, and as such, investors may have initially underestimated its importance as the IT revolution accelerated. While we expect variables such as R&D expenditures, patent approvals, and capital expenditures to also signal strong prospects, the fact that these indicators are widely used by investors and analysts suggests that they should be incorporated into stock prices on a timely basis. Using the notation of the model, we believe it is plausible that investors were fairly well informed about ebbs and flows in A, but at the same time, comparatively less informed about variation in α. This assumption forms the basis for why we are mostly interested in the ability of H-1B hiring to *forecast* future stock returns.

The second assumption is that as indicated in the joint subscripts pertaining to α, a firm's ability to extract value from its skilled workers varies not only across firms (i), but also across cities. Some of our empirical tests are designed to isolate variation in city-specific determinants of α, using proxies such as urban attributes that are likely to be attractive to potential H-1B hires. Importantly, the identifying assumption here does not rely on the distribution of asset-based value creation being identical across cities (e.g., $E(A_{Seattle} = E(A_{Philadelphia}))$, but rather that our empirical proxies for the city-based attributes represent a source of variation that is orthogonal to asset-based sources of value creation. In other words, even if the asset-based source of value creation in Seattle is fundamentally different from that in Philadelphia, as long as these differences are not systematically related to (say) the presence of an immigrant integration office, we can achieve causal identification.

3 Data

3.1 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),[6] 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 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 A1). 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 (2021, 2022), 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

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

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 A1).

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 (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.[7] 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. 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.

3.2 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).[8] To evaluate the degree of racial diversity of headquarter cities, we use the county-level population data by race from the U.S. Census' American Community Survey (ACS).[9] We use the ACS 2010 5-year estimates, which cover the data collected from January 2006 to December 2010.

[7] 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.

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

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

3.3 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 organizational capital employed by prior studies. Our final sample includes all NYSE, AMEX, and NASDAQ common stocks with CRSP share codes of 10 or 11.

4 Summary Patterns of H-1B Petitions

4.1 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.[10] Because firms during these years could not expect approval for all submitted petitions, there may have been an incentive to apply for more

[10]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 (2020) for a detailed characterization of how and why H-1B caps have evolved through time.

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: 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 each 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%.

4.2 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 $\mathit{H1BIntensity}_{i,t}$, defined as the logarithm of the number of H-1B applications made by firm i in year t ($\mathit{H1B}_{i,t}$) scaled by lagged (year $t-1$) total employment (COMPUSTAT item EMP).[11] Table 1 reports summary statistics for H-1B usage, as well as various auxiliary control variables. The unit of observation is the firm-year pair. Panel A characterizes the sample of firm-years involving

[11]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 $EMP_{\text{i,t-1}}$ prior to applying the log transformation.

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 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 (all defined in the Appendix). 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 organizational 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 capitalizations 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 quantile 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 employees 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.

5 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, the analysis includes standard controls for risk.

5.1 Stock Returns

5.1.1 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.[12]

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 4% in the first year after formation, with a t-statistic exceeding three. 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. Further robustness checks reported in Internet Appendix Table A2 show that when we exclude the largest firms with market capitalizations above the 90^{th} percentile of NYSE size breakpoint, the results remain robust. Thus, the finding is unlikely to be solely driven by the exceptional growth of large technology firms in recent years.

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 CRSP value-weighted index, the Fama-French 5-factor model, and a 6-factor model that adds a momentum factor. As shown in the table, the resulting alphas are around 4% to 5% and have t-statistics between two and three.

[12] For this benchmarking, we calculate value-weighted industry portfolio returns each month, using the Fama-French 17-industry categories.

5.1.2 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).[13] Lastly, we include the Fama-French 17-industry fixed effects. The results reported in Panel A of Table 4 are very similar to that in Table 3. The coefficients of *H1BIntensity* are positive and statistically significant at the 5% or 1% level 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.

Panel B shows the results of several robustness checks. Our results hold when using the Fama-French 49 industry classifications (instead of Fama-French 17), and when excluding firms located in New York or California. 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) or exclude the top 10% of firms with the highest H-1B hiring; in both cases, our findings remain robust. To examine whether variations in the denominator of the H-1B Intensity measure (total employees) influence our results, we include annual changes in total employees as a

[13]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 the Appendix.

predictor (no result); in another regression, we separately include H-1B hiring and total employees in the same model. The results suggest that the value creation effect is attributed specifically to H-1B workers. Additionally, the H-1B applications data from the U.S. Department of Labor does not include disclosure dates. To 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, 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 controls for R&D capital of Chan, Lakonishok, and Sougiannis (2001) and the cash-based operating profitability measure of Ball, Gerakos, Linnainmaa, and Nikolaev (2016). 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.

5.1.3 Cumulative 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. By December 2020, the nominal value of a dollar invested in the high H-1B investment had grown to over $10, about three times the value of the zero H-1B portfolio.

Panel B shows this comparison on an industry-adjusted basis. The blue 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 line, however, displays similar excess returns as in Panel A, though with lower absolute magnitude. The aggregate difference is about 90 percentage points (\$1.8 versus \$0.95) which, over the 147 months shown, suggests a return premium of about one-half percent per month, similar to the comparison shown in Table 3.

5.2 Fundamentals

As with any analysis of difference in excess returns, the patterns in the prior section can arise either from risk differences or unanticipated 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 Intensity, motivated by the idea that H-1B workers' created improvements in operational and/or technological efficiency will be eventually 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. The independent variables are firms' *H1BIntensity* and standard controls in fiscal year t. We also add industry×year fixed effects and cluster standard errors by firm.

Table 5 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 16% to 25% 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 ($p < 5\%$) roughly 2-3 years ahead. Here, a one-standard-deviation increase in *H1BIntensity* would increase earnings growth substantially by 225% to 275% relative to the mean (0.004, in Panel A of Table 1). Panel C coveys 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 growth of 72% to 92% 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.

5.3 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 are (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 use two methods employed in the literature. The first uses the actual date the earnings are reported (RDQ), which we obtain from the COMPUSTAT quarterly database. Returns on earnings announcement dates have a slight positive bias, because the fact that the earnings are announced on a particular day, rather than being delayed, is considered good news. To eliminate this bias, we follow the literature, e.g., Savor and Wilson (2016), and create an "anticipated" announcement date. When using the actual announcement date, we calculate the cumulative abnormal returns (in excess of the market factor) around the announcement date, *CAR* [-2, 1]. When using the anticipated announcements, we calculate the CAR during the same week of the anticipated date.

We run quarterly Fama-MacBeth regressions of abnormal returns around quarterly earnings announcement dates against H-1B Intensity. The *CAR* in each quarter is calculated as the cumulative return around each announcement date (either [-2, 1] or during the same week), normalized by the market return over the same horizon, and then summed across all earnings releases in the 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 similar as in Table 4, estimated either in fiscal year t–n or at the previous quarter end.

Table 6 reports the results. For both the actual and anticipated earnings dates, our results indicate that 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 0.05 to 0.07, 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 year 2 to year 3, and tailing off only slightly five years after the sort date, dovetailing with the humped-shaped pattern observed for two of the three operating measures in Table 5 (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 6 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 6 are 0.086 for year 2, 0.085 for year 3, and 0.07 for year 4, compared to 0.094, 0.084, and 0.062 in Table 4. However, the earnings response coefficients in Table 6 are measured over horizons four to five times shorter than that in Table 4, meaning that the return sensitivity to H-1B hiring is 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 6 with an indicator for a firm being in the top H-1B quintile. The coefficient on this dummy variable is about 0.5 (not tabulated), depending on the horizon and whether we use actual or anticipated earnings dates. This suggests that of the 4% average excess returns experienced by the highest H-1B quintile (relative to the other quintiles) in Table 3, about half (0.5% times four quarters) is realized during the few days surrounding quarterly earnings releases.

6 City and Firm Effects in Value Creation

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. Recall that the model presented in Section 2 classifies sources of value creation into two categories: 1) those arising from a firm's assets, and 2) those arising from a firm's people. As our model illustrates, while the high returns associated with the hiring of skilled labor may reflect 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 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. Specifically, we decompose the determinants of H-1B intensity into firm-specific, location-specific, and a residual component, and then regress future returns on the three separate components. This exercise reveals that although H-1B hiring is related to both firm and city-level attributes, the former (firm-level) attributes are *not* reliable predictors of stock returns. Rather, it is the city-level predictors of H-1B hiring, as well as the residual (i.e., the part of H-1B hiring unexplained by either firm- or city-level attributes), that forecast future returns. Given our assumption that the location attributes contribute to firm value only through the human capital channel, this result provides evidence that supports our hypothesis that observed excess returns reflect the superior ability of some firms to attract and utilize foreign talent.

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 is 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."[14] 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 3), we construct *AsianRatio* as the percentage of Asians (number of Asian residents scaled by total population) in the CBSA where the firm is headquartered.[15] Our assumption is that these variables capture an element of cross-sectional variation in H-1B hiring that should not be related to cross-sectional differences in growth opportunities that arise for reasons unrelated to the people the firm is likely to hire.

Table 7 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

[14] 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.`

[15] 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`

is a continuous variable of firms' *H1BIntensity*. We include year fixed effects, industry fixed effects, and industry×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 to 6), has the highest statistical significance among *all* variable, including firm characteristics. Doubling the percentage of Asians residing in a city – akin to moving from Portland, OR (5.6%) to Seattle, WA (11%) – is associated, on average, with a 25-30% increase in H-1B applications. The presence of an immigrant integration office (*ImmigrantOffice*) also provides explanatory power, although the results are stronger in the discrete choice models (columns 1 to 3).

The average city-level book-to-market ratio (*CityBM*) is generally not significant. However, city-level R&D capital (*CityRDC*), similarly aggregated across a firm's local peers, is positively related to a firm's propensity to hire H-1B workers.[16] 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, and those of their local neighbors.

6.2 H-1B Hiring Decomposition

Given the results of Table 7, we are now in a position to estimate the extent to which the various components of *expected* H-1B hiring forecast forecast future stock returns. To do this, we use the model in Table 7 to decompose firms' H-1B hiring intensity into expected

[16] 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), 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.

and residual components. Specifically, at the end of each fiscal year, we run the following cross-sectional regression:

$$\begin{aligned} H1BIntensity = {} & logMarketCap + logBM + AG + OperProfit + OrgCap + RDC \\ & + ImmigrantOffice + AsianRatio + CityBM + CityRDC \\ & + Industry\, Fixed\, Effects + \epsilon \end{aligned} \tag{4}$$

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 8 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*), capturing hiring in H-1B worker unexplained by firm or city characteristics, is statistically significant in four out of the five ensuing years. Finally, the expected component based on headquarter city attributes (*ExpectedH1BCity*) is generally the strongest forecasting variable, both economically and statistically.

The results have several implications. First, if the ability of H-1B hiring to forecast stock returns is due to a correlation with unobserved firm and industry prospects, these opportunities are orthogonal to conventional proxies for a company's growth potential. Second, since city attributes are likely to be orthogonal to the managers' private information, the private information channel cannot explain the excess returns associated with city attributes. Lastly, the estimated coefficients of the city component and residual component are of similar magnitude, indicating that the market tends to underreact equally to the future value created by those H-1B workers hired for no observable reason and those whose hiring can be explained by attributes of the headquarter city.

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. We re-estimate the same specification as in the first column of Table 4, but on different subsamples 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.[17]

Panel A of Table 9 reports the estimated regressions. The first three columns show the results for cities in the lowest, middle, and highest terciles, respectively, where cities are ranked by *H1BIntensityCity* from the prior fiscal year. Note that the size and significance of *H1BIntensity* is higher for the subsamples of firms in cities with greater H-1B intensities. Among cities in the lowest tercile of city-level H1-B hiring, there is only weak evidence that firm-level H-1B hiring is associated with future stock returns. However, the coefficient on *H1BIntensity* is significant in the middle tercile (0.08), and is stronger (0.10) among firms headquartered in the highest H-1B cities. Formalizing these differences in the final column, the coefficients on *H1BIntensity* and $H1BIntensity \times H1BIntensityCity$ are both positive and significant, and the magnitudes are similar. 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 every standard deviation of city-level H-1B hiring.

Note that the interaction term in column 4 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.

Panel B of Table 9 repeats the same specification, but with progressively longer lags of

[17]Note that a city's average (and rank) can change year to year.

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. Comparing these results with Table 4 (which does not explicitly consider city-level H-1B hiring), the results suggest that the market fails to recognize the *future* wealth created by firms that hire many H-1B workers, particularly when they are surrounded by neighboring firms doing the same.

The return differences described above are illustrated in Figure 3, Panel C. The double-sorted figure lends itself to a convenient interpretation. Starting with the grey line – low H-1B firms in cities with low average H-1B hiring – as a benchmark, we observe no abnormal stock performance. The blue line suggests that moving to a high H-1B city matters somewhat, but the effect is relatively small. More important is the firm's own H-1B hiring policy, which, as indicated by a comparison between the green and grey lines, more than doubles the blue-grey difference.

However by far, the best performance is observed for high H-1B firms headquartered in high H-1B cities (red line). This portfolio indicates a doubling of shareholder wealth over the sample period, well above any corresponding portfolio. Moreover, over the second half (roughly 2016 and beyond), note that the red-grey differential is higher than the *sum* of the blue-grey and green-grey differentials, consistent with a positive interaction between a firm's own H-1B hiring and that of its local neighbors.

There are two potential explanations for the above observation. The first is that firm's headquartered in high H-1B cities are able to attract the most talented H-1B workers. The second is that, perhaps because of knowledge spillovers, H-1B workers work more effectively in high H-1B cities. In either case, the result illustrates the value associated with locating in these talent hubs.

7 Presidential Election of 2016

Up to now, we have shown that firms having hired significant numbers of H-1B workers subsequently realized significantly positive excess stock returns. These excess returns are robust with respect to various risk benchmarks, and the returns are higher around earnings announcements. Our interpretation is that although firms benefit from hiring highly skilled foreign-born workers, financial markets initially underreacted to the value they create.

This final section provides further causal evidence that stock prices at least partially reflected the value of foreign-born talent during the 2016 U.S. Presidential election. 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.[18]

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 3-4 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.[19] 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%.[20] Hence, by virtually all measures, Trump's eventual victory represented a significant surprise to financial 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. Our hypothesis is that stocks best (least) positioned to benefit from Trump's presidency would experience positive (negative) returns around the realization of his election. 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. Note that relative to our prior tests, the identification assumption

[18]See "Trump: Only in favor of legal immigration", and "Donald Trump's flip-flop over H1B visa lands him in controversy".

[19]See Polls from RealClear Politics.

[20]See "Betting sites see record wagering on US presidential election".

here is relatively weak. For stock prices of the firms most exposed to the H-1B program to decline following the surprise election result, the market need only believe that H-1B workers contributed positively to firm values. In other words, it could still be the case that the surprise 2016 election result was bad news for high H-1B firms, but that on average, the market significantly undervalued these firms for extended periods of time (as we find).

To test this idea, we compare the returns of the portfolios of 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 0.07 (0.11) percent for the highest H-1B quintile, with a sample standard deviation of 0.46 (0.61) percent. Comparable estimates for the lowest quintile of H-1B firms are -0.03 (-0.05) percent of average returns with a sample standard deviation of 0.26 (0.35) percent. All of these return patterns are calculated net of each firm's FF-17 industry average.

We are interested in whether high H-1B firms' stock returns were especially poor in the days around the November 2016 election, relative to the portfolio-level volatility observed in the prior 180 days. Over the 3-day horizon immediately after the election, the returns of the highest H-1B quintile are -1.34 percent, deviating from the sample mean (0.07) by 1.41 percent, more than three times as large as the sample standard deviation of 0.46 percent. The 5-day return patterns are similar. Industry-adjusted returns for the highest H-1B portfolio are -1.77 percent, more than three times the sample standard deviation (0.61) away from the sample mean (0.11).

By comparison, neither the lowest quintile of H-1B firms (but excluding firms with zero H-1B workers), nor the "zero H-1B" portfolio, show any abnormal effect from Trump's surprise victory. The differential returns between the highest and lowest (zero) H-1B quintile over the 3-day window are -1.25 (-1.28) percent, deviating from the sample mean by 1.34 (1.37) percent, more than twice as large as the sample standard deviation of 0.63 (0.58) percent. The return patterns are similar over 5-day window. Figure 4 shows the results of these comparisons graphically, indicating a sharp drop in the day after the election for the highest H-1B portfolio only, and continuing to trend downward for several days thereafter.

It is worth reiterating that the low- and high-H-1B comparisons are net of industry effects, since all returns are benchmarked to their industry averages. Given our prior findings on city-level effects in stock returns (particularly related to H-1B visas), we have also explored whether the return patterns documented here represent city-level variation (e.g., changes in state or corporate tax rates) related to the Trump administration, but beyond any impact on immigration. It turns out that adjusting each firm's returns by the average returns of firms in their headquarter state (in addition to its industry counterparts), particularly in New York and California, strengthens the results, as indicated in Panel B of Table 10. Hence, Trump's election appeared to be perceived by the stock market as particularly bad for firms with the most exposure to the H-1B program, beyond the expected impact on particular industries or headquarter cities.

8 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 the tangible assets, e.g., property and equipment. The less tangible assets, like patents and brands, tend to be more difficult to value, and perhaps the most challenging is determining 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 more productive, employees than Firm B? And if they do have a more talented organization, does the firm 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 returns associated with the intense hiring of H-1B visa holders of about 4% per year. Given that these abnormal returns last for at least five years, superior talent appears capable of explaining a roughly 20% increase in the market capitalizations of high H-1B firms in our sample period.

As mentioned initially, we are not the first to explore the empirical linkage between organization capital and stock performance. Building upon seminal studies by Lev and Radhakrishnan (2005) and Eisfeldt and Papanikolaou (2013), our paper provides a new approach for estimating the value created by hiring talented employees.

Our identification strategy relies on city-level attributes that make some areas especially attractive to high value-added foreign labor, but are plausibly orthogonal to other determinants of firm performance. A second, related result is that the benefits of attracting high quality immigrant workers is especially high in cities that are especially attractive for immigrant talent. While this finding suggests that shareholders capture part of the surplus from these superior locations, further research that identifies the specific mechanism would be useful auxiliary evidence. In particular, it would be useful to identify whether firms in these cities benefit from local knowledge spillovers or whether these cities simply attract the best talent.

Our paper is also broadly related to the macro literature that attempts to quantify the share of value added captured by American labor. Since about 1980, the market capitalization of U.S. firms has grown considerably faster than the U.S. economy as a whole. This and collaborating evidence suggests that the “slice of the pie” accruing to shareholders has grown disproportionately to that captured by labor. This is in spite capital investments having declined over the same horizon. One explanation for this phenomenon is that the increased concentration of the U.S. economy has given large U.S. firms monopsony power that allows them to limit increases in worker salaries (Shapiro, 2019; Grossman and Oberfield, 2022). To an extent, our evidence is consistent with this explanation, but paints a relatively nuanced picture. We show that geography plays a key role, with firms in a few key cities reaping most of the benefits, and that what we observe is not purely a large firm phenomenon, with small firms also sharing in the surplus. Perhaps, further research will seek to tie these new facts to the broader literature on labor’s share of value added.

References

Agrawal, A., I. Hacamo, and Z. Hu, 2021, "Information Dispersion across Employees and Stock Returns," *Review of Financial Studies*, 34(10), 4785–4831.

Atkeson, A., and P. J. Kehoe, 2005, "Modeling and Measuring Organization Capital," *Journal of Political Economy*, 113(5), 1026–1053.

Ball, R., J. Gerakos, J. T. Linnainmaa, and V. Nikolaev, 2016, "Accruals, cash flows, and operating profitability in the cross section of stock returns," *Journal of Financial Economics*, 121(1), 28–45.

Belo, F., J. Li, X. Lin, and X. Zhao, 2017, "Labor-Force Heterogeneity and Asset Prices: The Importance of Skilled Labor," *Review of Financial Studies*, 30(10), 3669–3709.

Belo, F., X. Lin, and S. Bazdresch, 2014, "Labor Hiring, Investment, and Stock Return Predictability in the Cross Section," *Journal of Political Economy*, 122(1), 129–177.

Chan, L. K. C., J. Lakonishok, and T. Sougiannis, 2001, "The Stock Market Valuation of Research and Development Expenditures," *Journal of Finance*, 56(6), 2431–2456.

Chen, A., M. B. Zhang, and Z. Zhang, 2022, "Talent Retention Risk and Corporate Investment," Working paper, University of Southern California.

Chen, J., S. Hshieh, and F. Zhang, 2021, "The role of high-skilled foreign labor in startup performance: Evidence from two natural experiments," *Journal of Financial Economics*, 142(1), 430–452.

——— , 2023, "Hiring High-Skilled Labor through Mergers and Acquisitions," *Journal of Financial and Quantitative Analysis*, Forthcoming.

Cooper, M. J., H. Gulen, and M. J. Schill, 2008, "Asset Growth and the Cross-Section of Stock Returns," *Journal of Finance*, 63(4), 1609–1651.

Davis, J. L., E. F. Fama, and K. R. French, 2000, "Characteristics, Covariances, and Average Returns: 1929 to 1997," *Journal of Finance*, 55(1), 389–406.

Dimmock, S. G., J. Huang, and S. J. Weisbenner, 2022, "Give Me Your Tired, Your Poor, Your High-Skilled Labor: H-1B Lottery Outcomes and Entrepreneurial Success," *Management Science*, 68(9), 6355–7064.

Doran, K., A. Gelber, and A. Isen, 2022, "The Effects of High-Skilled Immigration Policy on Firms: Evidence from Visa Lotteries," *Journal of Political Economy*, 130(10), 2501–2770.

Dougal, C., C. A. Parsons, and S. Titman, 2022, "Urban Vibrancy and Value Creation," *Review of Financial Studies,* forthcoming.

Eisfeldt, A. L., E. Kim, and D. Papanikolaou, 2022, "Intangible Value," *Critical Finance Review*, 11(2), 299–332.

Eisfeldt, A. L., and D. Papanikolaou, 2013, "Organization Capital and the Cross-Section of Expected Returns," *Journal of Finance*, 68(4), 1365–1406.

Fama, E. F., and K. R. French, 2015, "A Five-Factor Asset Pricing Model," *Journal of Financial Economics*, 116(1), 1–22.

Ghosh, A., A. M. Mayda, and F. Ortega, 2014, "The Impact of Skilled Foreign Workers on Firms: An Investigation of Publicly Traded U.S. Firms," Working paper, Georgetown University.

Glennon, B., 2020, "How Do Restrictions on High-Skilled Immigration Affect Offshoring? Evidence from the H-1B Program," Working paper,.

Goyal, A., and S. Wahal, 2024, "R&D, Innovation, and the Stock Market," Working paper, Swiss Finance Institute.

Green, J., J. R. M. Hand, and X. F. Zhang, 2017, "The Characteristics that Provide Independent Information about Average U.S. Monthly Stock Returns," *Review of Financial Studies*, 30(12), 4389–4436.

Grossman, G. M., and E. Oberfield, 2022, "The Elusive Explanation for the Declining Labor Share," *Annual Review of Economics*, 14.

Hornbeck, R., and E. Moretti, 2024, "Estimating Who Benefits from Productivity Growth: Local and Distant Effects of City Productivity Growth on Wages, Rents, and Inequality," *Review of Economics and Statistics*, 106(3), 587–607.

Kerr, W. R., 2013, "U.S. High-Skilled Immigration, Innovation, and Entrepreneurship: Empirical Approaches and Evidence," Working paper, Harvard University.

Kerr, W. R., and W. F. Lincoln, 2010, "The Supply Side of Innovation: H-1B Visa Reforms and U.S. Ethnic Invention," *Journal of Labor Economics*, 28(3), 473–718.

Lev, B., and S. Radhakrishnan, 2005, "The Valuation of Organization Capital," in *Measuring Capital in the New Economy*, ed. by C. Corrado, J. Haltiwanger, and D. Sichel. University of Chicago Press, pp. 73–110.

Peri, G., K. Shih, and C. Sparber, 2015, "STEM Workers, H-1B Visas, and Productivity in US Cities," *Journal of Labor Economics*, 33(S1).

Peters, R. H., and L. A. Taylor, 2017, "Intangible capital and the investment-q relation," *Journal of Financial Economics*, 123(2), 251–272.

Prescott, E. C., and M. Visscher, 1980, "Organization Capital," *Journal of Political Economy*, 88(3), 446–461.

Savor, P. G., and M. I. Wilson, 2016, "Earnings Announcements and Systematic Risk," *Journal of Finance*, 71(1), 83–138.

Shapiro, C., 2019, "Protecting Competition in the American Economy: Merger Control, Tech Titans, Labor Markets," *Journal of Economic Perspectivess*, 33(3), 69–93.

Shen, M., 2021, "Skilled Labor Mobility and Firm Value: Evidence from Green Card Allocations," *Review of Financial Studies*, 34(10), 4663–4700.

Wu, A., 2018, "Skilled Immigration and Firm-Level Innovation: The U.S. H-1B Lottery," Working paper, Harvard Business School.

Xu, S.-J., 2021, "Skilled Labor Rationing, Hiring Uncertainty, and Corporate Investment: Evidence from H-1B Visa Application Deadlines," Working paper, University of Alberta.

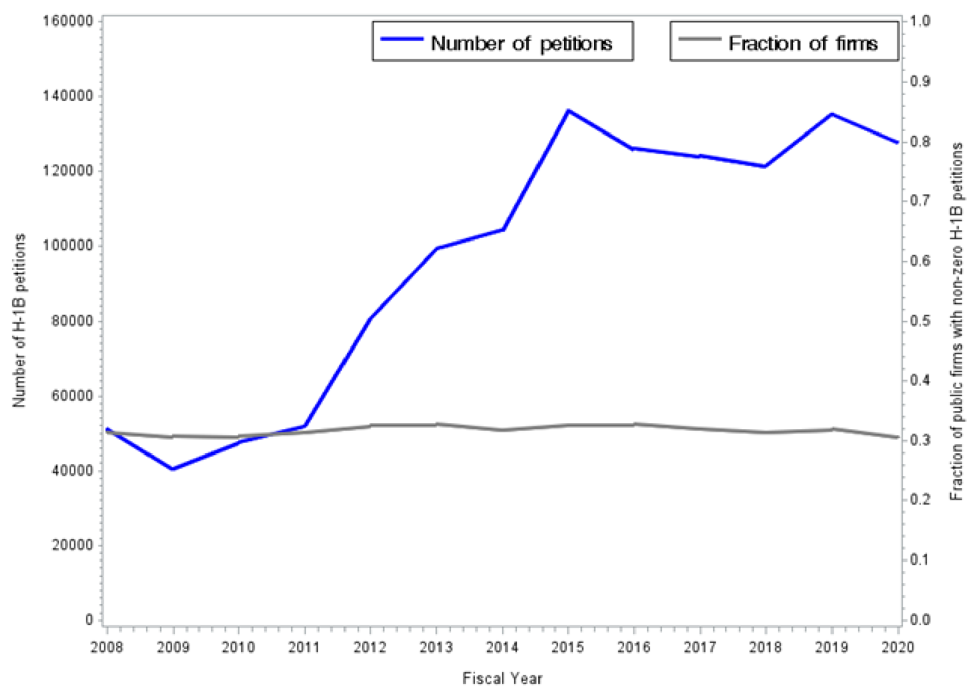
——— , 2022, "Skilled Foreign Workers and Corporate Investment: Evidence from the H-1B Visa Program," Working paper, University of Alberta.

Zhang, M. B., 2019, "Labor-Technology Substitution: Implications for Asset Pricing," *Journal of Finance*, 74(4), 1793–1839.

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

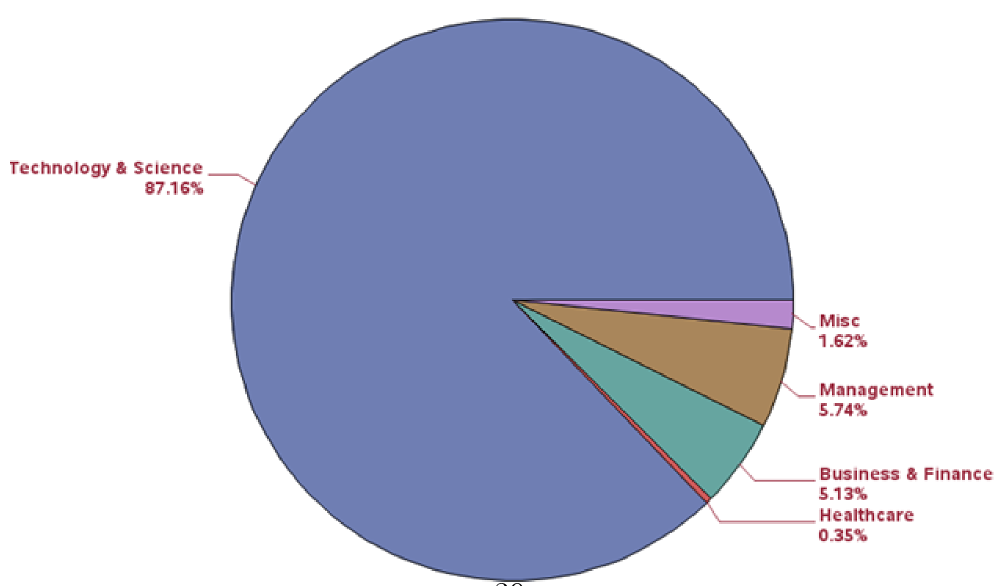


Figure 2: Geographic Distribution of H-1B Petitions

This figure plots the total number of H1B petitions filed by firms located in each core-based statistical area (CBSA) over 2008 to 2020 fiscal years.

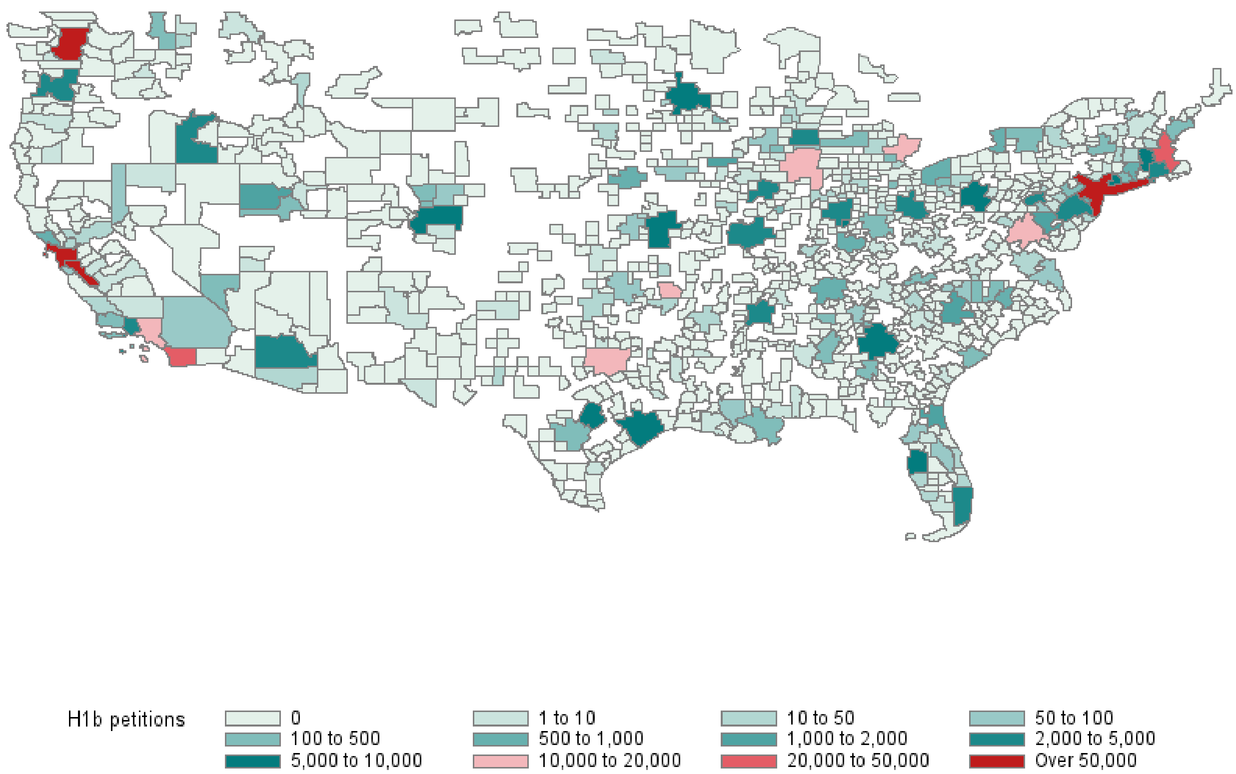
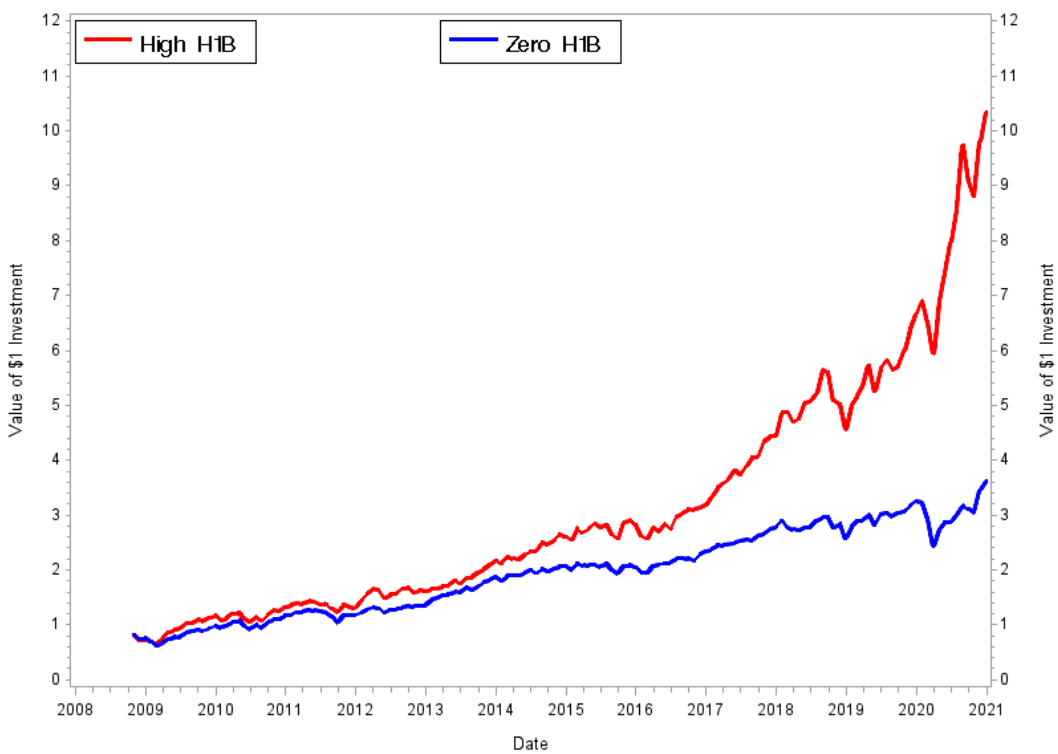


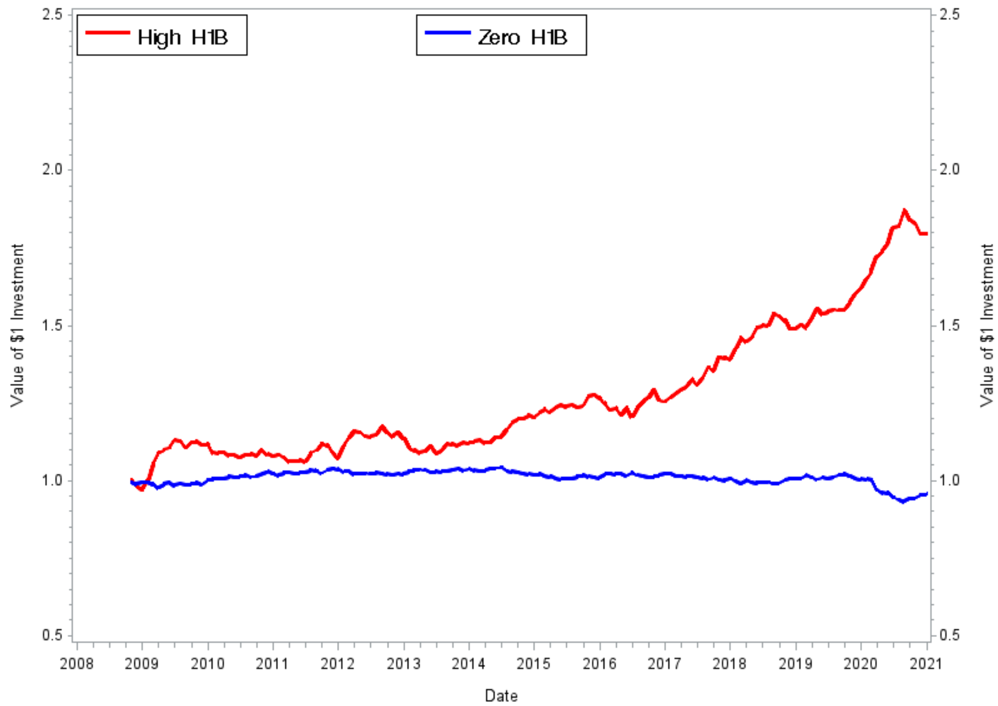
Figure 3: Value of $1 Investment in H-1B Portfolios

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 value of High and Zero portfolio based on raw stock returns, and Panel B uses industry-adjusted returns (Fama-French 17). Panel C compares the cumulative value 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)

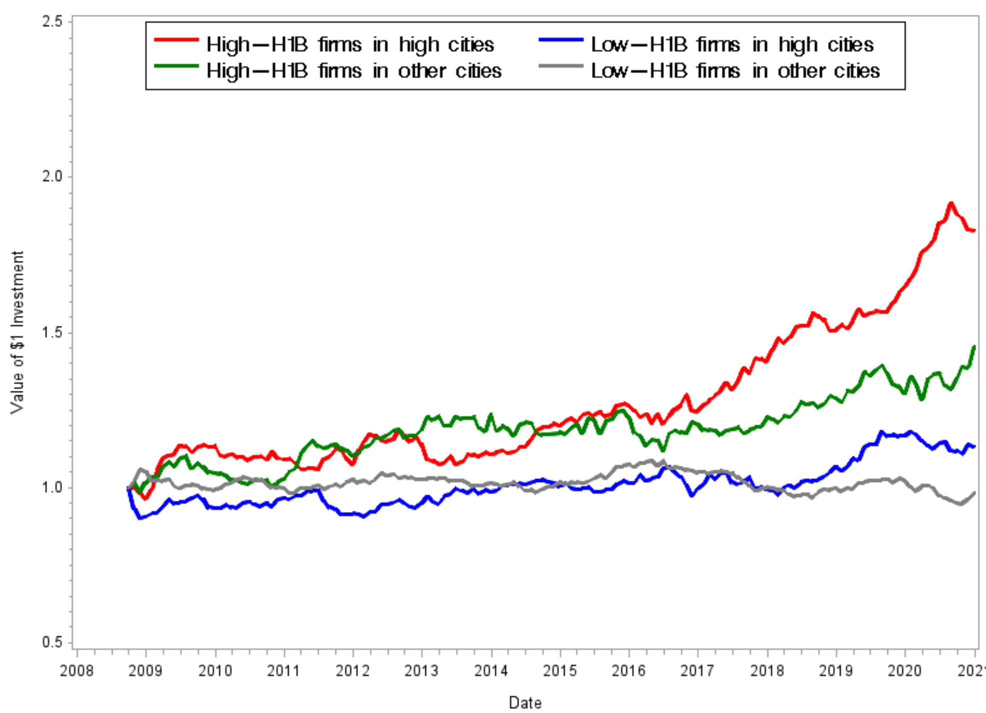
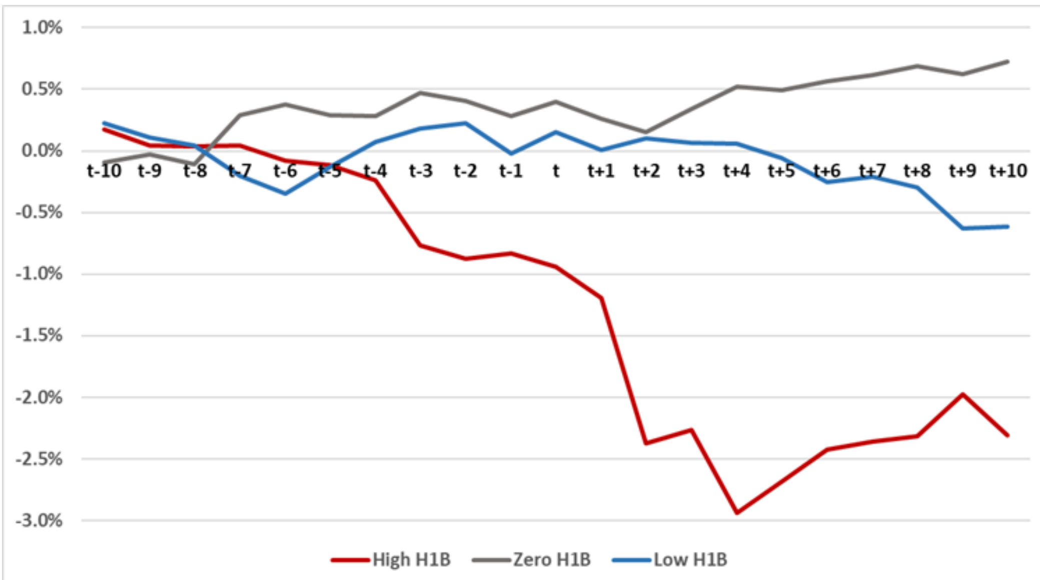


Figure 4: Event Study Around the Presidential Election of 2016

This figure plots the returns of H-1B portfolios around the presidential election of 2016. The election date was on November 8, 2016 (event date t). We measure the cumulative portfolio returns over 20 days before and after the election date, from October 25 (date t-10) to November 22 (date t+10), 2016. The High, Low, and Zero H-1B portfolios are constructed as in Table 3. Panel A plots the cumulative portfolio returns using industry-adjusted returns. Panel B provides a robustness check that further adjusts for the New York and California location effect by subtracting the average returns of all firms located in New York and California, respectively, from the industry-adjusted returns of firms located in these two states.

Panel A: Industry-adjusted returns



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

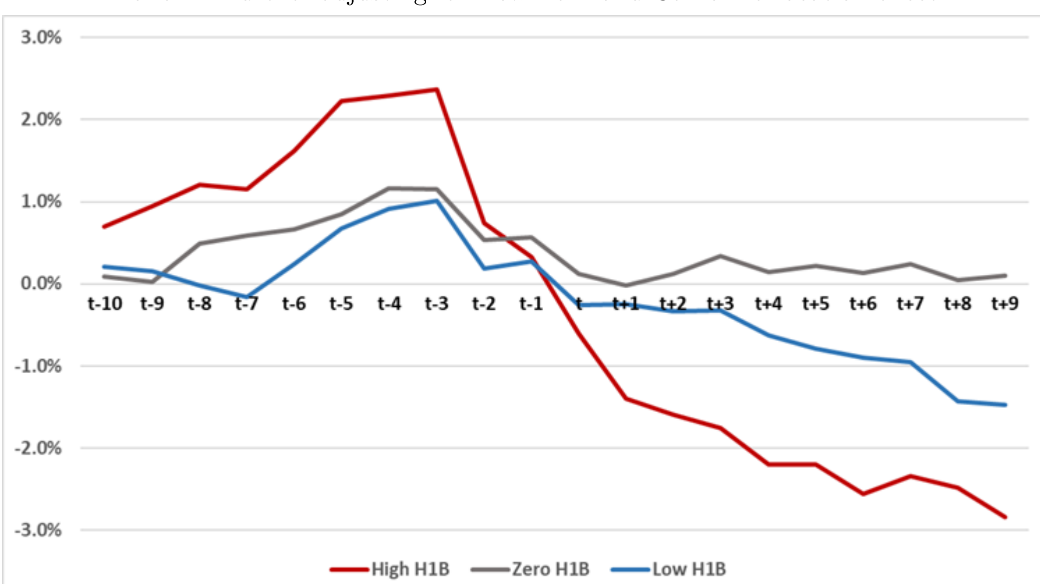


Table 1: Summary Statistics

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 petitions, 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 petitions

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
Book-to-Market	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
Asset Growth	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
R&D Capital	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
Book-to-Market	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
Asset Growth	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
R&D Capital	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 average of the ranking variable (*H1BIntensity*), the number 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 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 five-factor model (FF5), and the Fama-French five-factor model plus a momentum factor (FF6) to estimate monthly alphas. We calculate 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 the Fama-French 17-industry classification method). The sample period is 2008/10 to 2020/12.

Panel A: Annual (industry-adjusted) portfolio returns (%)

Portfolios	N firms	$t + 1$	$t + 2$	$t + 3$	$t + 4$	$t + 5$
Zero	2957.2	-0.70	-0.32	-0.51	-0.77	-0.88
		(-1.03)	(-0.49)	(-0.87)	(-1.40)	(-1.24)
Low	202.5	-0.12	-0.55	-1.13	-1.57	-1.68
		(-0.16)	(-0.52)	(-0.88)	(-1.15)	(-0.99)
2	201.9	-0.17	-0.53	-1.30	0.62	-3.16
		(-0.16)	(-0.87)	(-0.92)	(0.44)	(-1.38)
3	201.7	-2.54	-2.07	-0.61	-1.67	-0.41
		(-2.48)	(-1.56)	(-0.74)	(-1.46)	(-0.31)
4	202.0	-0.67	-0.25	-1.73	0.21	-1.05
		(-0.72)	(-0.15)	(-1.49)	(0.18)	(-0.87)
High	201.4	4.28	3.00	4.09	4.15	5.37
		(3.31)	(1.76)	(3.00)	(4.84)	(5.55)
High–Low		4.40**	3.55	5.22**	5.73**	7.06**
		(2.46)	(1.56)	(2.23)	(2.78)	(3.00)
High–Zero		4.98**	3.32	4.61**	4.92***	6.26***
		(2.66)	(1.42)	(2.42)	(3.80)	(4.28)

Panel B: Annualized (industry-adjusted) portfolio returns and alphas (%)

	Zero	Low	2	3	4	High	High–Low	High–Zero
Average return	-0.84	-0.36	-0.36	-2.64	-0.84	4.44	4.80**	5.28**
	(-1.28)	(-0.39)	(-0.31)	(-1.96)	(-0.65)	(2.78)	(2.25)	(2.53)
CAPM alpha	-0.96	-0.24	-0.72	-1.20	-0.96	4.32	4.56**	5.28**
	(-1.31)	(-0.25)	(-0.61)	(-0.90)	(-0.65)	(2.49)	(1.99)	(2.33)
FF5 alpha	-0.48	-0.60	-0.84	-1.44	0.00	3.48	4.08**	3.96**
	(-1.10)	(-0.71)	(-0.84)	(-1.11)	(0.04)	(2.66)	(2.34)	(2.43)
FF6 alpha	-0.48	-0.60	-0.96	-1.32	0.00	3.36	3.96**	3.96**
	(-1.10)	(-0.71)	(-0.93)	(-1.05)	(0.03)	(2.71)	(2.33)	(2.44)

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 to 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 organizational 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 17-industry classification method) to control for industry average returns. Panel A reports the main results. Panel B shows various robustness checks. Specifically, R&D capital (*RDC*) and cash-based operating profitability (*CbOP*) are defined in the Appendix. Changes in total employees (*logEMP_chg*) is the difference between the logarithm of total employees in the current year and the logarithm of total employees in the previous year. *logH1B* is the logarithm of the total number of H-1B petitions, and *logEMP* is the logarithm of total employees. 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: Main Results

	Dependent variable = Monthly returns in fiscal year t				
	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
H1BIntensity (t-n)	0.096***	0.094***	0.084**	0.062**	0.085**
	(3.67)	(2.73)	(2.47)	(2.09)	(2.46)
ZeroH1B (t-n)	-0.079	-0.083	-0.047	-0.121**	-0.071
	(-1.57)	(-1.55)	(-0.87)	(-2.51)	(-1.25)
logMarketCap (t-n)	-0.087	-0.091	-0.046	-0.032	-0.009
	(-0.84)	(-0.78)	(-0.43)	(-0.26)	(-0.07)
logBM (t-n)	0.035	0.018	0.042	0.086	0.001
	(0.42)	(0.21)	(0.56)	(0.97)	(0.01)
AG (t-n)	-0.161***	-0.040	-0.043	0.048	-0.083*
	(-4.40)	(-1.19)	(-0.90)	(0.93)	(-1.69)
OperProfit (t-n)	0.130	0.159**	0.139**	0.117*	0.021
	(1.60)	(2.61)	(2.47)	(1.89)	(0.28)
OrgCap (t-n)	-0.032	-0.014	-0.038	-0.046	0.006
	(-0.63)	(-0.27)	(-0.61)	(-0.72)	(0.12)
Beta	0.081	-0.024	-0.022	0.021	0.024
	(0.50)	(-0.17)	(-0.14)	(0.12)	(0.12)
Ret (t-12, t-2)	-0.242	-0.070	-0.049	-0.060	-0.060
	(-1.31)	(-0.72)	(-0.48)	(-0.55)	(-0.49)
Ret (t-36, t-13)	-0.031	0.040	0.080	0.099	0.094
	(-0.25)	(0.46)	(0.85)	(0.90)	(0.77)
Industry F.E.	Yes	Yes	Yes	Yes	Yes
Adj. R^2	6.3%	6.0%	6.1%	6.2%	6.4%
Observations	421,788	377,603	328,069	282,242	240,269

Panel B: Robustness Checks

	Dependent variable = Monthly returns in fiscal year t								
	FF 49 industry classifications	Removing NY and CA firms	Removing FAANG stocks	Removing top 10% H-1B firms	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
H1B_Intensity (t-1)	0.083***	0.068***	0.091***	0.097***	0.115***	0.085***	0.088***		
	(3.38)	(3.50)	(3.54)	(3.77)	(4.09)	(3.12)	(3.29)		
ZeroH1B (t-1)	-0.053	-0.051	-0.075	-0.082	-0.050	-0.060	-0.062		0.101
	(-1.25)	(-0.96)	(-1.50)	(-1.53)	(-0.95)	(-1.26)	(-1.07)		(1.35)
logMarketCap (t-1)	-0.092	-0.054	-0.090	-0.092	-0.102	-0.075	-0.095	-0.065	-0.161
	(-0.86)	(-0.53)	(-0.86)	(-0.89)	(-0.96)	(-0.75)	(-1.03)	(-0.67)	(-1.37)
logBM (t-1)	0.037	0.082	0.037	0.030	0.076	0.075	0.061	0.025	0.009
	(0.43)	(1.01)	(0.45)	(0.37)	(0.96)	(0.88)	(0.81)	(0.30)	(0.12)
AG (t-1)	-0.165***	-0.138***	-0.165***	-0.166***	-0.121***	-0.161***	-0.150***	-0.161***	-0.156***
	(-4.35)	(-3.39)	(-4.47)	(-4.86)	(-3.06)	(-4.44)	(-4.31)	(-3.81)	(-4.17)
OperProfit (t-1)	0.163**	0.145*	0.131	0.133	0.163**	0.193***		0.121	0.112
	(2.18)	(1.69)	(1.60)	(1.63)	(2.09)	(2.76)		(1.47)	(1.45)
OrgCap (t-1)	-0.044	-0.002	-0.033	-0.035	-0.011	-0.038	0.016	-0.017	-0.039
	(-0.86)	(-0.04)	(-0.65)	(-0.67)	(-0.22)	(-0.72)	(0.28)	(-0.32)	(-0.74)
RDC (t-1)						0.149			
						(1.47)			
CbOP (t-1)							0.233***		
							(2.84)		
logEMP_chg (t-1)								-0.001	
								(-0.02)	
logH1B (t-1)									0.125**
									(2.32)
logEMP (t-1)									0.059
									(0.82)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	7.0%	7.1%	6.3%	6.3%	6.2%	6.5%	6.4%	6.3%	6.4%
Observations	422,545	322,608	421,236	409,916	411,469	421,788	364,137	418,538	419,574

Table 5: 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* 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 include standard control variables as well the corresponding dependent variable (*DepVar*) in fiscal year t. 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)	0.014***	0.017***	0.020***	0.020***	0.013***
	(3.63)	(4.09)	(4.41)	(4.03)	(2.67)
ZeroH1B (t)	0.024**	0.004	-0.004	0.002	-0.016
	(2.20)	(0.34)	(-0.33)	(0.17)	(-1.11)
SalesGrowth (t)	-0.015	-0.011	0.024*	-0.020	0.006
	(-1.02)	(-0.76)	(1.71)	(-1.30)	(0.33)
logMarketCap (t)	0.060***	0.035***	0.011*	0.005	-0.016**
	(9.73)	(5.43)	(1.70)	(0.74)	(-2.16)
logBM (t)	-0.122***	-0.097***	-0.076***	-0.070***	-0.049***
	(-16.51)	(-11.55)	(-8.59)	(-7.16)	(-5.15)
Beta (t)	-0.016**	-0.013*	-0.001	-0.010	-0.015*
	(-2.56)	(-1.84)	(-0.09)	(-1.35)	(-1.91)
AG (t)	0.217***	0.052***	0.053***	0.030**	0.020
	(19.99)	(5.21)	(5.01)	(2.42)	(1.41)
OperProfit (t)	-0.097***	-0.053***	-0.026**	-0.029**	-0.028**
	(-9.65)	(-4.98)	(-2.42)	(-2.46)	(-2.37)
OrgCap (t)	-0.030***	-0.022**	-0.016*	-0.010	-0.017
	(-3.59)	(-2.37)	(-1.68)	(-0.88)	(-1.42)
Industry×Year F.E.	Yes	Yes	Yes	Yes	Yes
Adj R^2	13.6%	6.9%	5.5%	5.0%	4.9%
Observations	33,066	28,807	24,940	21,427	18,225

Panel B: Earnings Growth

	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
H1BIntensity (t)	0.002	0.009**	0.011***	0.003	0.005
	(0.51)	(2.55)	(3.05)	(0.89)	(1.34)
ZeroH1B (t)	0.022**	-0.015	-0.027**	-0.007	-0.024**
	(2.24)	(-1.49)	(-2.42)	(-0.58)	(-2.02)
EarningsGrowth (t)	-0.228***	-0.057***	-0.034**	-0.000	-0.049***
	(-19.47)	(-4.51)	(-2.52)	(-0.01)	(-3.06)
logMarketCap (t)	0.020***	-0.007	-0.009	0.008	0.006
	(3.75)	(-1.29)	(-1.61)	(1.44)	(1.04)
logBM (t)	-0.092***	0.042***	0.024***	0.018**	0.005
	(-11.01)	(5.50)	(3.04)	(2.07)	(0.53)
Beta (t)	-0.005	0.018***	0.005	-0.002	-0.006
	(-0.77)	(3.38)	(0.80)	(-0.30)	(-0.98)
AG (t)	-0.174***	-0.045***	0.012	0.013	0.003
	(-18.38)	(-4.92)	(1.11)	(1.24)	(0.27)
OperProfit (t)	-0.070***	-0.026**	0.003	0.006	-0.005
	(-6.00)	(-2.44)	(0.29)	(0.51)	(-0.39)
OrgCap (t)	0.034***	0.010	0.006	0.010	-0.001
	(3.36)	(1.19)	(0.69)	(1.04)	(-0.08)
Industry×Year F.E.	Yes	Yes	Yes	Yes	Yes
Adj R^2	12.1%	2.9%	2.1%	1.8%	2.2%
Observations	33,098	28,843	24,968	21,449	18,242

Panel C: R&D Growth

	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
H1BIntensity (t)	0.046***	0.036***	0.040***	0.037***	0.039***
	(8.43)	(5.85)	(6.13)	(5.44)	(5.56)
ZeroH1B (t)	-0.032***	-0.022	-0.016	-0.020	-0.030*
	(-2.65)	(-1.55)	(-1.00)	(-1.23)	(-1.69)
R&DGrowth (t)	0.091***	-0.000	0.015	0.016	0.028**
	(7.74)	(-0.02)	(1.30)	(1.22)	(2.17)
logMarketCap (t)	0.022***	0.030***	0.025***	0.012*	0.003
	(3.68)	(4.55)	(3.60)	(1.72)	(0.44)
logBM (t)	-0.067***	-0.072***	-0.061***	-0.049***	-0.037***
	(-8.97)	(-9.03)	(-7.08)	(-5.27)	(-3.82)
Beta (t)	0.006	-0.000	0.005	0.003	-0.008
	(0.93)	(-0.04)	(0.66)	(0.40)	(-1.06)
AG (t)	0.184***	0.079***	0.021**	0.003	0.022**
	(18.12)	(8.65)	(2.21)	(0.35)	(2.18)
OperProfit (t)	0.032***	0.012	-0.004	0.004	0.012
	(3.59)	(1.22)	(-0.33)	(0.35)	(0.99)
OrgCap (t)	-0.018**	-0.006	0.001	0.000	0.002
	(-2.07)	(-0.64)	(0.09)	(0.03)	(0.16)
Industry×Year F.E.	Yes	Yes	Yes	Yes	Yes
Adj R^2	8.7%	3.8%	2.7%	2.3%	2.1%
Observations	33,104	28,851	24,975	21,454	18,246

Table 6: 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. The key variable of interest is firms' H-1B intensity (*H1BIntensity*) in fiscal year $t - n$, where n equals 1 to 5. Control variables are similar as in Table 4, estimated either in fiscal year $t - n$ or in 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 around earnings announcements 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)
ZeroH1B (t-n)	-0.099	-0.151**	-0.123*	-0.206**	-0.185***
	(-1.51)	(-2.04)	(-1.78)	(-2.35)	(-2.86)
logMarketCap (t-n)	-0.109**	-0.084*	-0.058	-0.048	-0.051
	(-2.15)	(-1.71)	(-1.08)	(-0.81)	(-0.96)
logBM (t-n)	0.164**	0.160***	0.143**	0.183***	0.083
	(2.41)	(2.99)	(2.08)	(3.54)	(1.06)
AG (t-n)	-0.152***	-0.089***	-0.082***	0.014	-0.033
	(-6.06)	(-3.66)	(-2.77)	(0.40)	(-0.69)
OperProfit (t-n)	0.286***	0.283***	0.234***	0.199***	0.145*
	(4.74)	(4.72)	(4.45)	(3.01)	(1.88)
OrgCap (t-n)	0.041	0.017	-0.003	0.004	-0.029
	(0.65)	(0.36)	(-0.06)	(0.07)	(-0.47)
Beta	-0.011	-0.066	-0.037	0.018	0.018
	(-0.18)	(-1.14)	(-0.54)	(0.26)	(0.23)
Ret (t-12, t-2)	0.043	0.065	0.045	0.045	-0.007
	(0.71)	(1.09)	(0.63)	(0.50)	(-0.10)
Ret (t-36, t-13)	0.121*	0.164**	0.127*	0.170*	0.145
	(1.97)	(2.33)	(1.75)	(1.81)	(1.56)
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 the week of the anticipated earnings announcement date					
	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
H1BIntensity (t-n)	0.026	0.055**	0.069***	0.061**	0.065**
	(1.05)	(2.02)	(2.97)	(2.10)	(2.24)
ZeroH1B (t-n)	-0.070	-0.162	-0.186**	-0.159**	-0.108**
	(-1.06)	(-1.63)	(-2.54)	(-2.54)	(-2.04)
logMarketCap (t-n)	-0.069	-0.080	-0.070	-0.010	-0.016
	(-1.36)	(-1.61)	(-1.18)	(-0.17)	(-0.26)
logBM (t-n)	0.111*	0.102*	0.098	0.134**	0.023
	(1.99)	(1.85)	(1.45)	(2.05)	(0.28)
AG (t-n)	-0.157***	-0.007	-0.000	0.071*	0.009
	(-5.15)	(-0.19)	(-0.01)	(1.81)	(0.26)
OperProfit (t-n)	0.132**	0.167***	0.191***	0.151***	0.082*
	(2.47)	(3.33)	(4.77)	(4.04)	(2.01)
OrgCap (t-n)	0.032	-0.016	-0.015	-0.024	0.005
	(0.67)	(-0.57)	(-0.50)	(-0.58)	(0.13)
Beta	0.053	-0.049	-0.001	0.020	0.016
	(0.71)	(-0.79)	(-0.02)	(0.27)	(0.20)
Ret (t-12, t-2)	-0.103	-0.011	-0.012	0.011	-0.042
	(-1.27)	(-0.21)	(-0.23)	(0.19)	(-0.58)
Ret (t-36, t-13)	0.093*	0.115**	0.074*	0.121**	0.090
	(1.73)	(2.66)	(1.96)	(2.35)	(1.68)
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 7: 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×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***	0.501***	0.505***	0.011	0.105**	0.107**
	(20.13)	(19.82)	(19.80)	(0.23)	(2.24)	(2.26)
logBM	0.025	0.065***	0.063***	-0.151***	-0.088**	-0.086**
	(1.32)	(3.16)	(3.04)	(-4.00)	(-2.24)	(-2.16)
AG	-0.008	-0.009	-0.009	0.106***	0.087***	0.089***
	(-0.98)	(-1.02)	(-0.98)	(6.78)	(5.36)	(5.41)
OperProfit	0.080***	0.048***	0.048***	-0.045	-0.037	-0.035
	(5.18)	(2.84)	(2.81)	(-1.45)	(-1.14)	(-1.06)
OrgCap	0.246***	0.186***	0.189***	0.009	0.095**	0.093**
	(13.34)	(8.29)	(8.37)	(0.23)	(2.09)	(2.01)
RDC	0.109***	0.090***	0.088***	0.215***	0.182***	0.182***
	(6.08)	(4.25)	(4.12)	(5.24)	(4.27)	(4.19)
ImmigrantOffice	0.085**	0.085**	0.089**	0.088	0.075	0.080
	(2.38)	(2.23)	(2.33)	(1.30)	(1.12)	(1.17)
AsianRatio	0.128***	0.129***	0.129***	0.303***	0.246***	0.246***
	(5.70)	(5.09)	(5.09)	(7.94)	(5.94)	(5.86)
CityBM	-0.024	-0.022	-0.023	0.024	0.007	0.010
	(-1.30)	(-1.17)	(-1.22)	(0.65)	(0.21)	(0.27)
CityRDC	0.090***	0.040	0.040	0.204***	0.159***	0.161***
	(3.98)	(1.61)	(1.59)	(4.36)	(3.28)	(3.27)
Year F.E.	Yes	Yes	No	Yes	Yes	No
Industry F.E.	No	Yes	No	No	Yes	No
Industry×Year F.E.	No	No	Yes	No	No	Yes
Adj. R^2				21.2%	29.9%	29.4%
Observations	35,234	32,370	32,370	10,977	10,147	10,147

Table 8: 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 4 to decompose firms' H-1B intensity, using the firm-year sample with at least one H-1B petitions 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 17-industry classification method). *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 to 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)	0.114**	0.107**	0.116*	0.069	0.122*
	(2.32)	(2.25)	(1.84)	(1.07)	(1.66)
ExpectedH1BFirm (t-n)	0.057	0.063	0.050	0.120	0.170*
	(0.76)	(0.95)	(0.64)	(1.57)	(1.75)
ExpectedH1BCity (t-n)	0.166***	0.107*	0.113**	0.112**	0.134***
	(2.83)	(1.96)	(2.50)	(2.38)	(3.06)
Beta	0.046	-0.059	-0.070	-0.010	-0.044
	(0.21)	(-0.36)	(-0.40)	(-0.05)	(-0.22)
Ret (t-12, t-2)	-0.198	-0.028	0.108	-0.147	-0.112
	(-0.97)	(-0.32)	(1.13)	(-1.28)	(-0.75)
Ret (t-36, t-13)	0.095	0.178	0.231	0.200	0.125
	(0.61)	(1.46)	(1.45)	(1.38)	(0.66)
Adj. R^2	4.2%	3.6%	3.7%	3.9%	4.2%
Observations	109,117	97,648	85,216	73,582	62,783

Table 9: 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* $\times$ *H1BIntensityCity*. Low-, Mid- and High-H1B Cities are defined using the 33^{rd} and 67^{th} percentile of the distribution of *H1BIntensityCity*. The controls 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)	0.039	0.080**	0.104**	0.062***
	(1.00)	(2.12)	(2.29)	(3.22)
ZeroH1B (t-1)	-0.141	-0.020	0.034	-0.032
	(-1.43)	(-0.30)	(0.47)	(-0.81)
H1BIntensityCity (t-1)				0.034
				(1.23)
H1BIntensity$\times$*H1BIntensityCity (t-1)*				0.068**
				(2.49)
Controls	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	9.2%	6.9%	5.2%	6.3%
Observations	146,937	137,923	129,616	414,476

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)	0.071**	0.064**	0.039	0.059*
	(2.46)	(1.98)	(1.42)	(1.75)
ZeroH1B (t-n)	-0.046	-0.016	-0.074	-0.011
	(-0.93)	(-0.28)	(-1.37)	(-0.19)
H1BIntensityCity (t-n)	0.032	0.037	0.038	0.037
	(1.38)	(1.29)	(1.31)	(1.66)
H1BIntensity$\times$*H1BIntensityCity (t-n)*	0.044**	0.038**	0.051***	0.056***
	(2.13)	(2.03)	(2.78)	(3.13)
Controls	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	6.1%	6.1%	6.2%	6.4%
Observations	370,957	322,368	277,394	236,167

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 date was on November 8, 2016. We measure the post-election cumulative portfolio returns (on industry-adjusted basis) over 3 days from November 9 to November 11, CAR $(t+1,\ t+3)$, and 5 days from November 9 to November 15, CAR $(t+1,\ t+5)$. To estimate the sample mean and variance of the respective portfolio returns, we measure the cumulative (industry-adjusted) portfolio returns at the 3- and 5-day unit over the preceding 180 days, which gives 60 3-day portfolio returns and 36 5-day portfolio returns. We report the sample average 3-day and 5-day portfolio returns and standard deviations in the table. 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 provides a robustness check that further adjusts for the New York and California location effect by subtracting the average returns of all firms located in New York and California, respectively, from the industry-adjusted returns of firms located in these two states.

Panel A: Industry-adjusted returns

	Pre-election 180 days: 3-day CAR			Post election
H-1B Portfolio	N	Mean	Std	CAR $(t+1,\ t+3)$
High	60	0.07	0.46	-1.34
Low	60	-0.03	0.26	-0.09
Zero	60	-0.02	0.17	-0.05
High − Low	60	0.09	0.63	-1.25
High − Zero	60	0.09	0.58	-1.28

	Pre-election 180 days: 5-day CAR			Post election
H-1B Portfolio	N	Mean	Std	CAR $(t+1,\ t+5)$
High	36	0.11	0.61	-1.77
Low	36	-0.05	0.35	-0.21
Zero	36	-0.03	0.21	0.10
High − Low	36	0.16	0.88	-1.55
High − Zero	36	0.14	0.76	-1.86

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

	Pre-election 180 days: 3-day CAR			Post election
H-1B Portfolio	N	Mean	Std	CAR (t+1, t+3)
High	60	-0.09	0.90	-1.91
Low	60	-0.07	0.41	-0.61
Zero	60	-0.07	0.37	-0.44
High – Low	60	-0.02	0.72	-1.31
High – Zero	60	-0.03	0.69	-1.47

	Pre-election 180 days: 5-day CAR			Post election
H-1B Portfolio	N	Mean	Std	CAR (t+1, t+5)
High	36	-0.15	1.24	-2.52
Low	36	-0.12	0.59	-0.90
Zero	36	-0.11	0.52	-0.42
High – Low	36	-0.03	0.96	-1.63
High – Zero	36	-0.04	0.87	-2.11

Appendix: 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,

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

Organizational 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 A1: 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 A2: Robustness Checks for H-1B Intensity Portfolio Returns

This table performs robustness checks for the portfolio return results in Panel A of Table 3. We use the same portfolio formation methods as in Table 3, but exclude the largest firms with market capitalizations above the 90^{th} percentile of NYSE size breakpoint. We calculate the value-weighted average annual portfolio returns in each of the 5 years after ranking. All returns are industry-adjusted by the value-weighted industry average in each month (using the Fama-French 17-industry classification method). The sample period is 2008/10 to 2020/12.

Portfolios	N firms	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Zero	2651.5	0.10	0.15	-0.18	-0.39	-0.81
		(0.10)	(0.15)	(-0.15)	(-0.29)	(-0.46)
Low	177.7	0.85	0.56	0.73	0.06	0.33
		(0.90)	(0.40)	(0.49)	(0.04)	(0.22)
2	187.2	-1.52	-0.87	-2.94	-1.14	-1.13
		(-1.08)	(-0.70)	(-1.67)	(-0.72)	(-0.71)
3	182.6	0.58	-2.56	-0.93	-0.56	-1.19
		(0.40)	(-1.69)	(-0.56)	(-0.29)	(-0.46)
4	180.9	0.07	3.40	2.07	-0.41	-0.58
		(0.03)	(2.15)	(1.09)	(-0.21)	(-0.26)
High	171.9	4.55	2.89	2.35	4.19	5.60
		(3.77)	(2.79)	(1.89)	(2.82)	(3.14)
High−Low		3.70**	2.32	1.62	4.13**	5.28**
		(2.79)	(1.49)	(0.89)	(2.31)	(3.26)
High−Zero		4.45***	2.74**	2.53	4.58**	6.41***
		(3.08)	(2.21)	(1.66)	(2.92)	(5.81)