Give Me Your Tired, Your Poor, Your High Skilled Labor: H-1B Lottery Outcomes and Entrepreneurial Success

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Abstract

We study how access to high-skill labor affects firm-level outcomes for small innovative firms. We obtain exogenous variation in firms' ability to access skilled labor by using win rates in H-1B visa lotteries. Relative to firms that also applied for H-1B visas, but whose applications were not selected, firms that win in H-1B visa lotteries are more likely to receive additional venture capital funding or have an IPO. H-1B visa lottery winners also receive more patents and patent citations. Overall, our results show that access to high-skill labor is a critical determinant of success for small innovative firms.

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There is considerable debate about the desirability of allowing high-skill foreign workers to enter the country. Proponents argue that there is a shortage of high-skilled labor, creating a need for foreign workers. Accordingly, access to high-skilled foreign workers may benefit domestic firms, increasing investment and innovation. Yet, critics content that, instead of filling a skill gap, foreign workers merely displace American workers and have little effect on investment and innovation by firms. Despite the intense debate, there is little evidence on the effect of high-skill foreign workers on firm-level outcomes.

In the United States, for-profit firms can access high-skill foreign workers through the H-1B visa system. For each government fiscal year, there is a fixed quota of H-1B visas available.[1] During years in which the demand for H-1B workers exceeds the available quota of H-1B visas, the visas are allocated through a "lottery."[2] These H-1B visa lotteries provide an ideal setting to identify the causal effect of highly skilled foreign workers on the success of firms. These lotteries provide exogenous variation in the supply of H-1B visas across firms that are ex ante similar, which enables us to isolate the effect of high-skilled foreign labor on firms' outcomes without contamination from confounding factors.

Specifically, in this paper we exploit exogenous variation in firms' H-1B visa lottery outcomes to identify how access to high-skill foreign workers affects the success of venture capital (VC) funded start-up firms. Such VC funded firms depend heavily on the human capital of their employees. For such firms, high skill workers can contribute to the success of the firm

[1] The H-1B visa quota does not apply to hiring by universities and certain non-profit firms. In this paper, we study for-profit firms that are subject to the quota.
[2] U.S. Citizenship and immigration Services uses "a computer-generated random selection process" to allocate H-1B visas when applications exceed the quota. For example, see https://www.uscis.gov/news/alerts/uscis-completes-h-1b-cap-random-selection-process-fy-2019.

by increasing productivity and innovation. If high-skilled foreign workers are valuable assets for start-up firms, other things equal, access to foreign talent should lead to better firm outcomes.

We construct a sample of start-up firms in the Crunchbase dataset that file H-1B petitions for fiscal years in which the lotteries are held for all H-1B visas. We find that a higher win rate in H-1B lotteries positively predicts the likelihood of receiving funding, in the form of VC financing, a sizeable acquisition, or an IPO, during the next three years. This result is robust to controlling for a number of firm characteristics, such as the amount raised in prior funding rounds, the number of H-1B applications, and the average salary of the H-1B petitions. We further control for a host of fixed effects including industry-year and city-year fixed effects, or industry-city-year fixed effects. The economic magnitude of the result is large. For example, a one standard deviation increase in the win rate is associated with a 4.66 percentage point increase in the likelihood that the firm receives subsequent funding (a 32.7% increase relative to the baseline funding rate). Strikingly, the magnitude of this effect is little changed by the inclusion of controls or various fixed effects, indicating that the H-1B visa shock is random and uncorrelated with observable firm characteristics.

Since going public is the most desirable outcome for start-up firms (e.g., Brau, Francis, and Kohers, 2003), we examine the effect of H-1B visa lottery outcomes on the probability of an IPO. We find that firms with higher win rates in the H-1B lottery are significantly more likely to go public. The economic magnitude of this result is large. For example, a one standard deviation increase in the win rate is associated with a 0.98 percentage point increase in the probability of an IPO, representing a 23.4% increase relative to the baseline IPO rate.

Our data also enable us to observe the occupations for H-1B visa applicants. We therefore restrict the sample to firms whose applicants are all for the same occupation and further include occupation-year fixed effects in our regressions. In our most stringent specification, we essentially compare the funding outcome for firms with similar characteristics that are in the same industry, same city, and same year, and apply for foreign workers in the same occupation. We find that the magnitude of the coefficients is little changed compared to those in the baseline regressions. These results further mitigate the concern that our win rate measure might be correlated with unobserved factors that affect both the win rate and the funding outcomes.

We next examine one possible mechanism through which high-skill foreign workers could affect the outcomes of start-up firms – through their contribution to innovation. To test this, we match firms in our sample with patent data from the United States Patent and Trademark Office (USPTO) and construct five measures of innovation performance: an indicator for whether a firm applies for any patents that are later approved, the number of patents, the adjusted number of patents, the number of adjusted citations, and the average number of adjusted citations per patent. We find that the win rate in the H-1B visa lottery has a significant positive effect on innovation outcomes across the five measures. The economic magnitudes of the results are large. For example, a one standard deviation increase in the win rate is associated with a 6.3% increase in the number of patents and a 5.3% in the number of adjusted patent citations. These results suggest that highly skilled foreign workers contribute to the innovation success of start-up firms.

Our paper contributes to the literature on the economic impacts of high-skilled foreign workers. Kerr and Lincoln (2010) show that increases in the H-1B admission cap (at the national level) lead to increased patenting by Indians and Chinese in cities and firms that are more dependent on the H-1B program. However, using H-1B visa lotteries in two fiscal years during which only a relatively small fraction of the visas are allocated through lotteries, Doran, Gelber, and Isen (2016) find that winning additional H-1B visas generally has insignificant and at most modest effects on firms' patenting outcomes and that these H-1B workers substantially crowd out the employment of other workers. Peri, Shih, and Sparber (2015) show that negative shocks in the supply of H-1B visas induced by the lotteries at the city level lead to reduced employment growth in both foreign and domestic-born workers, suggesting a complementarity between the two. Our paper complements the existing studies by using the variation in the supply of H-1B visas at the firm level for four years when all H-1B visas are allocated through lotteries and focusing on the funding and patenting outcomes of start-up firms.

Our study has important policy implications. The findings that a higher win rate in H-1B visa lotteries leads to improved funding and patenting outcomes of start-up firms suggest that foreign talents do not simply displace domestic U.S. workers at start-up firms, but rather bring valuable human capital that is otherwise hard to obtain by these firms. Thus, our results, suggest that a more open immigration policy on highly skilled workers may be warranted as it aids in the development of small innovative firms.

The rest of the paper is organized as follows. Section 1 discusses the background on H-1B visa lotteries. Section 2 describes our data sources and reports summary statistics. Section 3 presents our main empirical results. Section 4 contains robustness tests related to occupational categories. Section 5 presents results for patenting and innovation, and Section 6 concludes.

1. Background on H-1B Visas

The purpose of the H-1B visa is to allow U.S. employers to hire skilled foreign workers in specialty occupations "that requires (a) theoretical and practical application of a body of highly specialized knowledge and (b) attainment of a bachelor's or higher degree in the specific specialty (or its equivalent) as a minimum for entry into the occupation in the United States" (U.S.C. ∮1184(i)(1)). An H-1B visa permits the holder to work in the U.S. for three years, renewable up to a total of six years, and the employer can sponsor the H-1B visa holder for permanent residency.

For an individual to receive an H-1B visa they must have an offer of employment from a U.S. firm. The firm must file a Labor Condition Application (LCA) with the Department of Labor, stating that the employment offer complies with the requirements of the H-1B visa program. The LCA includes information about the firm, such as its name, address, and industry. The LCA also includes information about the position, such as the salary, starting date, job title, and Standard Occupational Classification (SOC) code.[3]. If the Department of Labor certifies the LCA, the potential employee may apply for an H-1B visa by submitting an I-129 petition to U.S. Citizenship and Immigration Services (USCIS).

The number of H-1B visas available to for-profit firms is capped in each federal government fiscal year (beginning on October 1 and ending September 30 of the subsequent year). During our sample period, the quota of available new H-1B visas was capped at 65,000 per fiscal year (the regular cap), with an additional quota of 20,000 H-1B visas available for individuals who hold a master's degree or Ph.D. from an eligible and accredited U.S. university (the master's cap). The quotas apply only for new H-1B applications (not renewals or transfers between employers) made by for-profit firms (e.g., universities are not subject to the cap).

LCAs can be filed up to six months before the employment starting date and typically take at least a week to be approved. The USCIS begins processing applications on April 1 for positions beginning in October of that year, and continues to process applications until that year's quota has been filled. Because of the sequential approval process, firms frequently "pre-date" LCA applications by filing LCAs in January, February, or March, giving a start date that is

[3] The Standard Occupational Classification system was created by the Bureau of Labor Statistics to assign standardized codes for jobs. See https://www.bls.gov/soc/.

six months in the future. Pre-dated and approved LCAs can then be used to file I-129 petitions immediately at the beginning of April, effectively front-running applicants who wait until April to apply for an LCA. See Peri, Shih, and Sparber (2015) for further discussion of pre-dating.

For fiscal years 2008, 2009, and each fiscal year beginning from 2014 onward, *all* new H-1B visas were allocated by USCIS lotteries using "a computer-generated random selection process," because the quota of available H-1B visas was oversubscribed within the filing period (i.e., the first five business days of April preceding the fiscal year).[4] In other years, because the cap was reached after the filing period, the majority of the visas were granted on a first-come, first-served basis. In each year when the cap was reached within the filing period, USCIS first conducted a lottery to assign the 20,000 H-1B visas available under the master's cap. After this lottery, the unselected applicants from the master's cap lottery are pooled with the applicants who are not eligible under the master's cap, and a second lottery is conducted to assign the remaining 65,000 H-1B visas. Thus, individuals eligible for the master's cap pool have a higher probability of receiving an H-1B visa relative to ineligible applicants.

2. Data and Variables

Our study combines data from multiple sources. First, we obtain data on H-1B visa applications and approvals from the Department of Labor and U.S. Citizenship and Immigration Services (USCIS). Second, we identify a set of private start-up companies, and obtain data on these companies, from Crunchbase. Finally, we obtain data on patents from the public use PatentsView data files, made available by the United States Patent and Trademark Office (USPTO).

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[4] For example, see https://www.uscis.gov/news/alerts/uscis-completes-h-1b-cap-random-selection-process-fy-2019.

To construct our sample of firm-fiscal year observations, we begin with the set of Crunchbase firms that meet the following criteria: (1) is not public as of the beginning of the fiscal year, (2) has completed at least one round of financing, and (3) the dollar amount of the prior financing is available. Using firm names and addresses, we match the Crunchbase firms to the H-1B data and retain the firms that applied for at least one H-1B visa as described earlier. There are 1,998 unique firms meeting these criteria and 2,800 firm-year observations. Consistent with prior studies of start-ups, such as Wang (2017), the firms in our sample are concentrated in a few states: 48.9% in California, 9.9% in Massachusetts, and 8.8% in New York.

2.1. H-1B Visa Data

We obtain data on approved H-1B applications from USCIS through a Freedom of Information Act (FOIA) request. The data provide the number of new H-1B applications that are approved by USCIS for each employer in each government fiscal year. Our analyses focus on fiscal years 2008, 2009, 2014, and 2015, because in these fiscal years all new H-1B visas were granted through lotteries. In contrast, for fiscal years 2010-2013 there was less demand for new H-1B visas and most applications were not subject to a lottery.

We obtain data on companies' Labor Condition Applications (LCA) from the Department of Labor.[5] The data provide detailed information for each H-1B application, including job information such as the job title, occupation, salary, and the intended starting and ending dates; employer information such the firm's name, address, and NAICS code; and the status of the application (i.e., whether it is certified, withdrawn, or denied). Following Peri, Shih, and Sparber (2015), we use the number of certified LCAs for H-1B visas filed by a firm in January through April with a start date that is five to six months in the future as a proxy for the firm's

[5] The data are available at https://www.foreignlaborcert.doleta.gov/performancedata.cfm.

demand for new H-1B workers in the upcoming fiscal year. Even with the requirement that the start date is five to six months in the future, our sample of LCAs will include some applications that are for either renewals or transfers of existing H-1B visa holders instead of for new H-1B visas. Table 1 shows that the average firm in the sample applies for 2.7 H-1B visas, but this variable is positively skewed; 57% of the sample applies for a single visa and only 3.7% apply for more than five.

We divide the number of approved new H-1B visas by the number of applications to create our key explanatory variable, *Win Rate*. Table 1 shows the average *Win Rate* for firms in the sample is 29%. We note that this is somewhat lower than the lottery success rates provided by the USCIS, as the denominator of the *Win Rate* variable (the number of applications) contains some applications for renewals and transfers of H-1B workers who are already employed in the U.S.

In the LCA filing, companies are required to state the salary offered to the H-1B visa candidate. For companies that file multiple LCAs in a given fiscal year, we take the average of the reported salaries. As Table 1 shows, the average (median) salary offered to the H-1B candidates is $85,128 ($80,434). Because salary is related to the economic value of the employee to the company, in our tests we control for the natural logarithm of salary.

2.2. Crunchbase Data

We obtain data on start-up firms from Crunchbase, a crowd-sourced database that tracks events related to start-up companies, especially those in high-tech sectors. As of December 2017, the dataset covers over 113,000 firms and more than 280,000 events (including private funding rounds, IPOs, and acquisitions). For each start-up firm, the data provide the name, address, and industry of the firm and detailed information on the events (e.g., the date, type, and amount of a funding round and the date of an IPO or acquisition). To ensure the Crunchbase data for the firm is sufficiently detailed, we limit our sample to firms that have completed at least one round of prior financing and report the dollar amount of prior financing. Because our focus is on start-ups, we exclude firms that have already gone public. We then match firms in the Crunchbase data with employers in our H-1B data using names and addresses.

A number of recent studies have examined the Crunchbase data and its reliability. Dalle, den Besten, and Menon (2017) compare the Crunchbase database with the OECD Entrepreneurship Financing Database and with the VentureXpert database, and conclude that "…the coverage is very comprehensive, especially for start-ups located in the United States." Ling (2016) manually compares transaction amounts for a subsample of Crunchbase firms with data from business publications and VentureXpert, and finds that the Crunchbase data are accurate. Wang (2017) argues that Crunchbase is the best available data source for early stage innovation.

From the Crunchbase data we create several control variables. The summary statistics in Table 1 show that firms in the sample have completed an average of 2.8 prior rounds of financing, have received an average of $39.6 million in prior external financing, had their first financing round 56.4 months ago, and the most recent round 26.7 months ago.

Using the Crunchbase data, we create three dependent variables based on indicators of firm success. All variables are based on events that occur during the three year period beginning in October of the year of the H-1B lottery. First, following Hochberg, Ljungqvist, and Lu (2007), we use receiving additional funding, either from additional venture capital funding or an IPO, as an interim measure of a firm's success. Additional venture capital funding is a reasonable interim signal of the firm's success. Venture capital funds typically fund portfolio companies using staged financing; to allow the VC to cut its losses easily, VCs typically provide limited funding, monitor the portfolio company, and provide additional funding only if the company's performance is satisfactory (Gompers, 1995; Tian, 2011).[6] Second, as is common in the literature, we use having an initial public offering (IPO) as a measure of success. Third, following Bernstein, Giroud, and Townsend (2016) we use being acquired for at least $25 million as a measure of success. The $25 million cutoff is to screen out acquisitions that do not represent successful exits.

From these three types of events we create three dependent variables. *Funded* is an indicator variable equal to one for the 49.2% of firms that received additional venture capital financing, had an IPO, or were acquired. *IPO* is an indicator variable equal to one for the 4.2% of firms that had an IPO. Exit is an indicator variable equal to one for the 9.7% of firms that had a successful exit – either via IPO or an acquisition.

2.3. Patent Data

A large number of prior studies use the number of patents and patent citations as measures of innovative success,[7] and numerous studies show these variables are correlated with the value of innovation.[8] To examine innovation in our sample, we obtain patent data from the USPTO data tables provided through PatentsView,[9] and match Crunchbase firms to the patent assignee identifiers in the PatentsView data using firm names and locations. The PatentsView

[6] Similarily, Kerr, Lerner, and Schoar (2014) use receiving venture capital funding as a measure of success for angel funded firms.
[7] Lerner and Seru (2017, Appendix 1) list 68 papers that use patent data published in the top three finance journals from 2005-2017.
[8] For example, see Pakes (1985), Griliches (1990), Trajtenberg (1990), Austin (1993), Hall, Jaffe, Trajtenberg (2005), and Kogan, Papanikolaou, Seru, and Stoffman (2017).
[9] The PatentsView data tables are available at http://www.patentsview.org/download/. In this paper, we use the data files as of the May 28, 2018 update. The advantage of the PatentsView database is that it is regularly updated. In contrast, other patent databases, such as the NBER patent database, do not include data for recent years.

dataset includes information on all patents granted between January 1976 and December 2017, including information about technology classes and citations. For each approved patent, the dataset provides both the application date and the approval date. We match the Crunchbase and H-1B sample to the PatentsView data using firm names and locations.

Using the PatentsView data, we create several dependent variables that measure the firms' innovative output. Each of these variables is based on approved patents that the firm applied for during the three year period that the H-1B visa applied for would be valid.[10] In the regressions, we control for lagged values of the dependent variable, based on the three year period before the H-1B visa lottery application period.[11]

Following the literature, we adjust both the number of patents and the number of citations based on the year of application and technology category. Hall, Jaffe, and Trajtenberg (2001, 2005) argue that un-adjusted patent variables are subject to truncation bias and are not directly comparable across time or technology categories. Truncation bias in the number of patents occurs because we observe only approved patent applications. Patent approval takes an average of two years but can take considerably longer (e.g., see Dass, Nanda, and Xiao (2017) and Lerner and Seru (2017)). As a result, recent patent applications that are still undergoing the approval process are unobservable. Truncation bias in the number of citations occurs because patent citations accumulate over time; thus, citation counts are not comparable across patents of different vintages. Further, patent counts and citations are not directly comparable across different technological categories, because of differences in patenting rates, approval rates, and

[10] For example, for fiscal year 2008 our dependent variable would include patents applied for during the period October 1, 2007 thought September 30, 2010, because this is the period during which the H-1B visa holder would be allowed to work for the firm.
[11] For example, for fiscal year 2008 the USCIS began accepting applications on April 1, 2007. Accordingly, the control variables are based on approved patents applied for during the period April 1, 2004 through March 31, 2007.

typical citation life-cycles, among other reasons (see Dass, Nanda, and Xiao (2017) and Lerner and Seru (2017)).

To adjust for these problems, we follow Hall, Jaffe, and Trajtenberg (2001, 2005), Lerner, Sørensen, and Strömberg (2011), Bena and Li (2014), and Seru (2014) and adjust both the number of patents and citations per patent. We adjust the number of patents as follows. First, for each technology category and year, we compute the average number of patents per firm (conditional on the firm having at least one patent in the category-year). Second, we scale each patent by the average found in the first step. Third, we sum the scaled number of patents across all (approved) patents applied for by the firm in that year. Similarly, we adjust the citations per patent by first computing the average number of citations per patent in a given technology class-year. Second, we scale the citations per patent using this average. Third, we sum the scaled citations per patent across all (approved) patents applied for by the firm in that year.[12]

The summary statistic in Table 1 show that 32% of the firms in our sample have at least one patent in the three year period following inclusion in our sample and the average number of patents is 5.4. Patent numbers are highly skewed, however, with less than 1% of the firms responsible for half of the approved patents.

3. Main Results

3.1. H-1B Visa Lottery Outcomes and Additional Financing

The dependent variable in Table 2 is *Funded*, an indicator variable equal to one hundred if the company receives additional venture capital funding, is acquired for at least $25 million, or

[12] Recently, Dass, Nanda, and Xiao (2017) and Lerner and Seru (2017) document that these adjustment methods are less effective towards the end of any given sample period (when truncation issues are more severe). As an additional robustness test, in Internet Appendix Table 2 we replicate all patent results using only data from the 2008 and 2009 fiscal years.

has an IPO during the three year period beginning October 1 following the H-1B visa lottery. The specifications in the table become progressively more stringent moving from left to right. In column (1), the specification does not include any controls or fixed effects. The remaining columns include the following controls: log($ amount raised previously), log(months since first round), log(months since last round), log(number of H-1B applications), and log($ salary for H-1B position). The remaining columns also include fixed effects to absorb the number of prior rounds of financing and the type of prior financing (e.g., angel, series A, etc.). Column (2) includes year fixed effects. Column (3) includes, year, industry (two-digit NAICS code),[13] and city fixed effects. Column (4) includes industry-year and city-year fixed effects. And column (5) includes industry-city-year fixed effects. All columns report *t*-statistics based on standard errors clustered by firm.

In all specifications, the results show that firms with a higher *Win Rate* in the H-1B lottery are significantly more likely to receive additional venture capital funding or have an IPO in the subsequent three years. Further, the economic magnitude of the result is large. For example, the coefficient in column (3) implies that a one standard deviation increase in *Win Rate* is associated with a 4.66 percentage point increase in the likelihood the firm is funded (a 32.7% increase relative to the baseline funding rate).

The coefficient estimates are stable and consistent across the specifications in Table 2. In column (1), the regression does not include any controls whatsoever. In this regression, the result shows how variation in *Win Rate* affects the likelihood of receiving additional funding among all firms and years in the sample. In column (5), the regression includes numerous control variables as well as industry-city-year fixed effects. In this regression, the comparison

[13] Internet Appendix Table 1 shows that the results are robust to using fixed effects based on four-digit NAICS codes instead of two-digit.

group is limited to other firms that operate in the same industry and are located in the same city during the same year. Further, this regression controls for many of the firms' characteristics and its H-1B application profile. These fixed effects and controls explain a large portion of the variation in *Funded*; the *R*-squared increases from 0.023 to 0.354. The coefficient on *Win Rate*, however, is not significantly different across the two columns. Thus, to the extent that there is measurement error in the denominator of the *Win Rate* variable, it must be largely uncorrelated with industry, year, location, or other observable characteristics of the firms.

3.2. IPO and Exit Results

Following prior studies, in Panel A we use whether a firm has an IPO in the three year outcome period as a measure of firm success (see Hochberg, Ljungqvist, and Lu (2007), Sørensen (2007), Kerr, Lerner, and Schoar (2014), and Bernstein, Giroud, and Townsend (2016)). In Panel B, we use whether a firm has either an IPO or is acquired for at least $25 million as the dependent variable (see Bernstein, Giroud, and Townsend (2016)). Aside from the change in the dependent variable, the specifications reported in Table 3 are identical to those in the prior table; column (1) does not include any control variables or fixed effects and the remaining columns include both controls and increasingly more stringent fixed effects.

In all columns of Panel A, the coefficient on *Win Rate* is positive and significant. Firms that win visas in the H-1B lottery are significantly more likely to have an IPO. The economic magnitude of this result is large. For example, the coefficient in column (3) implies that a one standard deviation increase in *Win Rate* is associated with a 0.98 percentage point increase in the probability of an IPO (23.4% increase relative to the baseline IPO rate).

Similarly, in all columns of Panel B the coefficient on *Win Rate* is positive and significant. Firms that win visas in the H-1B lottery are significantly more likely to have an IPO or be acquired. The coefficient in column (3) implies that a one standard deviation increase in *Win Rate* is associated with a 1.26 percentage point increase in the probability of a successful exit (13.0% relative to the baseline rate).

4. Occupational Categories

As discussed in Section 1, there are two separate pools for the H-1B lottery. First, applicants with an approved U.S. graduate degree are entered into a lottery for the 20,000 "masters cap" visas. Second, the non-selected masters cap applicants are pooled with the non-masters cap applicants in a second lottery for the remaining 65,000 visas. Thus, H-1B applicants eligible for the master cap pool have a higher winning probability. Unfortunately, neither the LCA data nor the USCIS FOIA data indicate whether an applicant was entered in the master cap pool. We can, however, examine how applicant education correlates with variables in the LCA data using the education information that is included in the prevailing wage determination (PWD) data files provided by the Department of Labor (available for the 2014 and 2015 fiscal years). As part of the LCA process, firms must certify that the salary offered to the foreign worker will be at least as large as the "prevailing wage" offered to native workers with similar qualifications in the same occupational category. The firm must support its claim with reference to a prevailing wage determination source, such as the PWD program.

We examine the PWD data[14] and find that our baseline fixed effects absorb much of the variation in applicant education. Columns (2) and (4) of Internet Appendix Table 3 show that the industry-year and MSA-year fixed effects and the industry-MSA-year fixed effects absorb, respectively, 46.7% and 52.7% of the variation in applicant education. We find that including

[14] The PWD data sample we use includes only filings related to H-1B visas. We exclude filings by universities and other educational institutions, hospitals, clinics, medical institutions, and research instituions. We also exclude filings for medical doctors and dentists.

occupation category[15] fixed effects are also strongly related to applicant education. Column (1) of Internet Appendix Table 3 shows that occupation-year fixed effects alone explain 22.2% of the variation in applicant education, and column (5) shows that combining occupation-year and industry-MSA-year fixed effects can explain 63.5% of the variation in applicant education. Accordingly, we estimate robustness tests that include occupation code-year fixed effects. Given the strong relation between occupation code and applicant education, these fixed effects would absorb much of the potential effect that master cap applicants could have on the *Win Rate* variable.

For these tests, we exclude all observations for which the firm applied for H-1B visas in more than one occupation code. As a result, the sample size is smaller for these tests. For the sake of comparability, the odd numbered columns in Table 4 report results without occupation code-year fixed effects but estimated on the restricted sample. The even numbered columns report results that include occupation code-year fixed effects. We report three specifications. In columns (1) and (2), the model does not include any controls or fixed effects. In columns (3) and (4), the model includes firm controls as well as industry-year and city-year fixed effects. In columns (5) and (6), the model includes firm controls and industry-city-year fixed effects.

In the regressions reported in Panel A of Table 4, the dependent variable is *Funded*. The results are similar for all three specifications. Even with the inclusion of the occupation code-year fixed effect, there is a significant positive relation between *Win Rate* and *Funded*. Further, comparing the columns with and without the occupation code-year fixed effects shows that the inclusion of these fixed effects has little effect on the coefficient estimate.

[15] For the 2008 and 2009 fiscal years all applications include an LCA Occupation Code. By the 2014 and 2015 fiscal years, the LCA applications required employers to use the Bureau of Labor Statistics' Standard Occupational Classification system. See https://www.bls.gov/soc/ for further information.

In Panels B and C of Table 4, the dependent variables are *IPO* and *Exit*, respectively. Similar to the prior panel, including the occupation code-year fixed effects does not decrease the significance or the magnitude of the *Win Rate* coefficient. Overall, given the strong relation between occupation code and applicant education, the results in this section suggest that our inability to observe whether an applicant was included in the masters cap pool is unlikely to bias our findings.

5. Patenting and Innovation

The results in Table 5 show the relation between *Win Rate* and several variables measuring innovation. For each dependent variable, we report for five specifications with the fixed effects and controls becoming increasingly stringent moving from left to right. The fixed effects and controls are the same as in the baseline specifications reported in Tables 2 and 3, except in this table we also include the lagged value of the dependent variable as a control,[16] because past patenting activity is a strong predictor of future activity. Internet Appendix Table 2 reports robustness results using only data for the 2008 and 2009 fiscal years; the results are similar except as noted below.

In Panel A of Table 3, the dependent variable is *Any Patents*, an indicator variable equal to one if the firm applied for any patents (that were later approved) during the three-year post lottery period. In all specifications, there is a significant positive relation between *Win Rate* and *Any Patents*. Further, the economic magnitude of the result is large. For example, the coefficient in column (3) implies that a one standard deviation increase in the *Win Rate* increases

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[16] The lagged values of the dependent variables are measured over the three year period ending just before the H-1B lottery is held (e.g., for the government fiscal year 2009 results, the control variables are measured over the period April 1, 2005 through March 21, 2008).

the likelihood of receiving at least one patent by 2.5 percentage points (a 7.9% increase relative to the mean).

In Panels B and C, the dependent variables are the natural logarithms of the number of patents and of the adjusted number of patents, respectively. For both dependent variables, there is a strong positive relation between *Win Rate* and the number of patents, and the implied economic magnitudes of the results are large. For example, in column (3) of Panel B the results imply that a one standard deviation increase in the *Win Rate* is associated with a 6.3% increase in the number of patents. Internet Appendix Table 2 shows that, for both dependent variables, their relation with Win Rate was larger if the sample is restricted to the 2008 and 2009 government fiscal years (when truncation bias is less severe).

In Panel D, the dependent variable is the natural logarithm of the number of adjusted citations. The results show that a higher *Win Rate* is associated with significantly higher patent citations. For example, the results in column (3) imply that a one standard deviation increase in the *Win Rate* is associated with a 5.3% increase in the number of adjusted patent citations.

The total number of citations for a firm can increase either because the number of patents increases or because the citations per patent increase. To separate these two possibilities, in Panel E the dependent variable is the natural logarithm of the average number of adjusted citations per patent. The results show a positive relation between *Win Rate* and the average number of citations, but the significance is marginal in some columns and the results in Internet Appendix Table 2 are not significant for this dependent variable. Further, the magnitude of the coefficient estimates are small. Overall, the results in Table 3 suggest that Win Rate is positively related to the number of patents but has little effect on the number of cites per patent.

Our findings for patenting are consistent with those of Kerr and Lincoln (2010) who find a strong positive relation between H-1B visas and patenting, and more generally with Bernstein, Diamond, McQuade, and Pousada (2018) who find that immigrants are responsible for nearly a quarter of U.S. patents. But our results differ from those of Doran, Gelber, and Isen (2016) who find little relation between firms' H-1B visa approvals and the number of patents. In addition to differences in sample periods, Doran et al. examine the full universe of U.S. firms using data provided by the Internal Revenue Service (IRS). In contrast, we focus on a set of particularly innovative firms that appear in Crunchbase and have received prior venture capital funding. Indeed, the firms in our sample are nearly three times more likely to patent than the firms in Doran et al. The difference between our results and Doran et al. does suggest that the contributions of H-1B visa holders likely vary across firms, and the effects found in our sample of innovative firms are likely larger than would be found in the overall universe of firms.

6. Conclusion

In the U.S., firms can apply for H-1B visas that allow high-skill foreign workers to enter the U.S. There is a fixed quota of H-1B visas available to for-profit firms, and when the applications exceed the quota the U.S. government holds a lottery that assigns H-1B visas based on computer-generated pseudo-random numbers. The outcomes of these H-1B visa lotteries provides exogenous, random variation in firms' ability to access skilled foreign workers. In this paper, we examine a sample of small innovative firms that applied for H-1B visas, and compare outcomes based on the firms' win rate in the H-1B lotteries.

We find that a firm's win rate in the H-1B visa lottery is strongly related to the firm's outcomes over the following three years. Relative to comparable firms that also applied for H-1B visas, firms with higher win rates in the lottery are more likely to receive additional venture capital funding, have an IPO, or be acquired for a significant amount of money. Firms with higher win rates also receive more patents and more patent citations. Overall, the results show that access to skilled foreign workers is strongly associated with firm-level measures of success.

Our study has important policy implications. The results show that access to skilled foreign workers leads to improved funding and patenting outcomes for innovative start-up firms, suggesting that improved visa access for such firms could generate significant economic benefits.

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Figure 1

This figure illustrates the timeline of our study. H-1B visa lotteries for fiscal year *t* are held in the first week of April of fiscal year *t*-1, which is when the win rate is observed. We measure the funding and patenting outcomes during the three-year period starting from October 1 of fiscal year *t* (i.e., the earliest start date of employment for workers granted an H-1B visa in the lotteries for fiscal year *t*). We measure the control variables as of March 30 in fiscal year *t*-1.

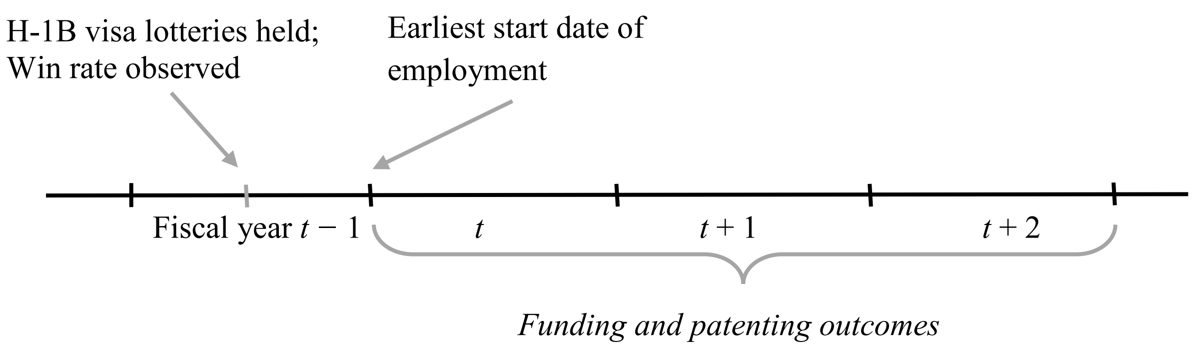

Table 1
Summary Statistics

This table reports the summary statistics for our sample of firm-years. The sample includes start-up firms in Crunchbase that sponsor H-1B petitions in fiscal years 2008, 2009, 2014, and 2015. *Number of Applications* is the number of applicants sponsored by a firm in a year. *Win Rate* is the number of H-1B visas a firm wins through the lotteries in a year divided by the number of applicants. *Salary* is the average annual salary of the applicants sponsored by a firm in a year. *Number of Prior Financing Rounds* is the number of funding rounds a firm receives before the lottery. *Prior amount Raised* is the total amount of funds raised before the lottery. *Time Since First Round* is the number of months between the first round of funding and the lottery. *Time Since Last Round* is the number of months between the most recent round of funding and the lottery. *Funded* is an indicator that equals 1 if a firm receives subsequent venture capital funding, has an IPO, or is acquired for at least $25 million during the three years following the lottery and zero otherwise. *IPO* is an indicator variable that equals one if the firm goes public in the three years following the lottery and zero otherwise. *Exit* is an indicator variable that equals one if the firm goes public or is acquired for $25 million or more in the three years following the lottery. *Any Patents* is an indicator variable that equals one if the firm is granted a patent in the three years following the lottery and zero otherwise. *Number of Patents* is the number of patents granted to a firm in the three years following the lottery. *Number of Adjusted Patents* is the category-year mean adjusted number of patents. *Total Citations* is the number of citations to a firm's patents granted in the three years following the lottery. *Total Adjusted Citations* is the category-year mean adjusted number of citations summed across the firm's patents. *Average Number of Citations* is the average number of citations to a firm's patents granted in the three years following the lottery. *Average Adjusted Number of Citations* is the average of the category-year mean adjusted citations on the firm's patents. For each variable, we report the mean, standard deviation, 25th percentile, median, and 75th percentile.

	Mean	Std. Dev.	25th%	Median	75th%
Number of Applications	2.69	6.85	1	1	2
Win Rate	0.29	0.41	0	0	0.54
Salary ($) winsorized at 99th%	85,128	27,726	65,450	80,434	100,000
Number of Prior Financing Rounds	2.77	2.02	1	2	4
Prior Amount Raised ($M)	39.57	87.66	5.01	17.0	44.11
Time Since First Round (months)	56.40	41.84	24	47	82
Time Since Last Round (months)	26.71	30.75	7	15	34
Funded$_{(t,t+2)}$ (×100)	49.21	50.00	0	0	100
IPO$_{(t,t+2)}$ (×100)	4.21	20.10	0	0	0
Exit$_{(t,t+2)}$ (×100)	9.71	29.62	0	0	0
Any Patents$_{(t,t+2)}$	0.32	0.47	0	0	1
Number of Patents$_{(t,t+2)}$	5.40	62.84	0	0	1
Number of Adjusted Patents$_{(t,t+2)}$	0.92	9.36	0	0	0.24
Total Citations	189.80	2074.18	0	0	8
Total Adjusted Citations	6.18	66.32	0	0	0.30
Average Number of Citations	9.88	36.30	0	0	3.61
Average Adjusted Number of Citations	0.32	1.17	0	0	0.13

Table 2
Win Rate and the Probability of Receiving Subsequent Funding

This table reports regression analysis of the effect of win rate in H-1B visa lotteries on the probability of receiving subsequent funding. The dependent variable is *Funded*, which equals one if a firm receives subsequent funding in the three years following the lottery and zero otherwise. The main independent variable is *Win Rate*, which is the number of H-1B visas a firm wins through the lotteries in a year divided by the number of applicants. Columns 2 through 5 include the following firm controls: log($ amount raised previously), log(months since first round), log(months since last round), log(number of H-1B applications), log($ salary for H-1B position), and fixed effects for the number of rounds of prior financing and for the type of prior financing. Numbers in square brackets are *t*-statistics based on standard errors clustered by firm.

	(1)	(2)	(3)	(4)	(5)
Win Rate	18.192 ***	16.026 ***	16.116 ***	19.343 ***	18.944 ***
	[8.22]	[7.61]	[7.04]	[7.32]	[6.25]
Firm Controls	No	Yes	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	--	--
Industry F.E. & City F.E.	No	No	Yes	--	--
Industry-Year F.E.	No	No	No	Yes	--
City-Year F.E.	No	No	No	Yes	--
Industry-Year-City F.E.	No	No	No	No	Yes
R^2	0.023	0.163	0.277	0.323	0.354
Adjusted R^2	0.022	0.151	0.179	0.163	0.157
Number of Obs.	2,800	2,800	2,800	2,800	2,800

Table 3
Win Rate and the Probability of IPO or Successful Exit

This table reports regression analysis of the effect of win rate in H-1B visa lotteries on the probability of going public. In Panel A, the dependent variable is *IPO*, which equals one if a firm goes public in the three years following the lottery and zero otherwise. Iin Panel B, the dependent variable is *Successful Exit*, which is an indicator variable set to one if the firm goes public or is acquired for at least $25 million in the three years following the lottery. The main independent variable is *Win Rate*, which is the number of H-1B visas a firm wins through the lotteries in a year divided by the number of applicants. Columns 2 through 5 include the following firm controls: log($ amount raised previously), log(months since first round), log(months since last round), log(number of H-1B applications), log($ salary for H-1B position), and fixed effects for the number of rounds of prior financing and for the type of prior financing. Numbers in square brackets are *t*-statistics based on standard errors clustered by firm.

Panel A: IPO					
	(1)	(2)	(3)	(4)	(5)
Win Rate	4.513 ***	3.381 ***	3.403 ***	3.845 ***	4.390 ***
	[3.99]	[3.24]	[3.17]	[3.13]	[3.42]
Firm Controls	No	Yes	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	--	--
Industry F.E. & City F.E.	No	No	Yes	--	--
Industry-Year F.E.	No	No	No	Yes	--
City-Year F.E.	No	No	No	Yes	--
Industry-Year-City F.E.	No	No	No	No	Yes
R^2	0.009	0.067	0.175	0.244	0.278
Adjusted R^2	0.008	0.054	0.063	0.066	0.058
Number of Obs.	2,800	2,800	2,800	2,800	2,800

Panel B: Successful Exit					
	(1)	(2)	(3)	(4)	(5)
Win Rate	7.047 ***	5.311 ***	4.363 ***	4.763 ***	4.998 ***
	[4.49]	[3.58]	[2.88]	[2.83]	[2.60]
Firm Controls	No	Yes	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	--	--
Industry F.E. & City F.E.	No	No	Yes	--	--
Industry-Year F.E.	No	No	No	Yes	--
City-Year F.E.	No	No	No	Yes	--
Industry-Year-City F.E.	No	No	No	No	Yes
R^2	0.010	0.075	0.223	0.272	0.307
Adjusted R^2	0.009	0.062	0.117	0.100	0.097
Number of Obs.	2,800	2,800	2,800	2,800	2,800

Table 4
Occupation-Year Fixed Effects as Additional Controls

This table reports regression analysis of the effect of win rate in H-1B visa lotteries on subsequent funding outcomes controlling for occupation-year fixed effects. The dependent variable in Panel A is an indicator for whether the firm receives subsequent funding in the three years following the lottery. The dependent variable in Panel B is an indicator for whether the firm goes public in the three years following the lottery. The dependent variable in Panel C is an indicator for whether the firm goes public or is acquired for at least $25 million in the three years following the lottery. The main independent variable is *Win Rate*, which is the number of H-1B visas a firm wins through the lotteries in a year divided by the number of applicants. Columns 3 through 6 include the following firm controls: log($ amount raised previously), log(months since first round), log(months since last round), log(number of H-1B applications), log($ salary for H-1B position), and fixed effects for the number of rounds of prior financing and for the type of prior financing. The odd numbered columns do not include occupation-year fixed effects but require that the observations have non-missing occupation classification codes. Numbers in square brackets are *t*-statistics based on standard errors clustered by firm.

Panel A: Probability of Receiving Subsequent Funding						
	(1)	(2)	(3)	(4)	(5)	(6)
Win Rate	15.723 ***	16.698 ***	17.846 ***	18.593 ***	18.382 ***	19.959 ***
	[6.49]	[6.46]	[5.78]	[5.52]	[5.09]	[5.11]
Firm Controls	No	No	Yes	Yes	Yes	Yes
Industry F.E. & City F.E.	No	No	--	--	--	--
Industry-Year F.E.	No	No	Yes	Yes	--	--
City-Year F.E.	No	No	Yes	Yes	--	--
Industry-Year-City F.E.	No	No	No	No	Yes	Yes
Occupation-Year F.E.	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**
R^2	0.018	0.100	0.339	0.395	0.349	0.407
Adjusted R^2	0.018	0.027	0.151	0.128	0.122	0.093
Number of Obs.	2,057	2,057	2,057	2,057	2,057	2,057

Panel B: Probability of IPO												
	(1)		(2)		(3)		(4)		(5)		(6)	
Win Rate	3.033	***	3.177	***	2.722	**	3.166	**	3.555	***	4.306	***
	[2.82]		[2.88]		[2.11]		[2.33]		[2.59]		[3.04]	
Firm Controls	No		No		Yes		Yes		Yes		Yes	
Industry F.E. & City F.E.	No		No		--		--		--		--	
Industry-Year F.E.	No		No		Yes		Yes		--		--	
City-Year F.E.	No		No		Yes		Yes		--		--	
Industry-Year-City F.E.	No		No		No		No		Yes		Yes	
Occupation-Year F.E.	**No**		**Yes**		**No**		**Yes**		**No**		**Yes**	
R^2	0.005		0.083		0.290		0.370		0.289		0.387	
Adjusted R^2	0.005		0.008		0.087		0.093		0.041		0.063	
Number of Obs.	2,057		2,057		2,057		2,057		2,057		2,057	

Panel C: Successful Exit												
	(1)		(2)		(3)		(4)		(5)		(6)	
Win Rate	5.139	***	5.400	***	3.546	*	4.259	**	3.846	*	4.978	**
	[3.10]		[3.02]		[1.91]		[2.01]		[1.77]		[2.01]	
Firm Controls	No		No		Yes		Yes		Yes		Yes	
Industry F.E. & City F.E.	No		No		--		--		--		--	
Industry-Year F.E.	No		No		Yes		Yes		--		--	
City-Year F.E.	No		No		Yes		Yes		--		--	
Industry-Year-City F.E.	No		No		No		No		Yes		Yes	
Occupation-Year F.E.	**No**		**Yes**		**No**		**Yes**		**No**		**Yes**	
R^2	0.006		0.091		0.294		0.368		0.293		0.368	
Adjusted R^2	0.006		0.017		0.092		0.090		0.047		0.034	
Number of Obs.	2,057		2,057		2,057		2,057		2,057		2,057	

Table 5
Win Rate and Patenting Outcomes

This table reports regression analysis of the effect of win rate in H-1B visa lotteries on patenting outcomes. For Panels A through E the dependent variable are, respectively: *Any Patent*, log(1 + *Number of Patents*), log(1 + *Adjusted Number of Patents*), log(1 + *Number of Adjusted Citations*), and log(1 + *Average Number of Adjusted Citations*). All dependent variables are measured over the three years following the lottery. The main independent variable is *Win Rate*, which is the number of H-1B visas a firm wins through the lotteries in a year divided by the number of applicants. Columns 2 through 5 include the following firm controls: log($ amount raised previously), log(months since first round), log(months since last round), log(number of H-1B applications), log($ salary for H-1B position), and fixed effects for the number of rounds of prior financing and for the type of prior financing. All columns include the patent activity of the firm over the three years prior to the lottery as a control (i.e., a lag of the dependent variable as defined in that specification), because past patenting activity is a strong predictor of future activity. Numbers in square brackets are *t*-statistics based on standard errors clustered by firm.

Panel A: *Any Patents*					
Win Rate	0.066 ***	0.059 ***	0.062 ***	0.067 ***	0.081 ***
	[3.65]	[3.34]	[3.27]	[2.97]	[3.07]
R^2	0.341	0.369	0.469	0.478	0.492
Adjusted R^2	0.340	0.360	0.397	0.355	0.337
Panel B: log(1 + *Number of Patents*)					
Win Rate	0.159 ***	0.150 ***	0.153 ***	0.185 ***	0.199 ***
	[4.43]	[4.39]	[4.10]	[4.24]	[4.18]
R^2	0.600	0.625	0.679	0.676	0.682
Adjusted R^2	0.599	0.620	0.635	0.600	0.585
Firm Controls	No	Yes	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	--	--
Industry & City F.E.	No	No	Yes	--	--
Industry-Year F.E.	No	No	No	Yes	--
City-Year F.E.	No	No	No	Yes	--
Industry-Year-City F.E.	No	No	No	No	Yes
Number of Obs.	2,800	2,800	2,800	2,800	2,800

Panel C: log(1 + *Adjusted Number of Patents*)					
Win Rate	0.086 ***	0.084 ***	0.086 ***	0.106 ***	0.104 ***
	[4.41]	[4.50]	[4.18]	[4.51]	[4.47]
R^2	0.635	0.659	0.701	0.688	0.699
Adjusted R^2	0.635	0.630	0.660	0.614	0.607
Panel D: log(1 + *Number of Adjusted Citations*)					
Win Rate	0.127 ***	0.120 ***	0.127 ***	0.183 ***	0.175 ***
	[3.86]	[3.89]	[3.57]	[4.49]	[4.09]
R^2	0.613	0.633	0.681	0.691	0.706
Adjusted R^2	0.613	0.628	0.638	0.618	0.616
Panel E: log(1 + *Average Number of Adjusted Citations*)					
Win Rate	0.023 **	0.020 *	0.022 *	0.037 **	0.036 **
	[2.01]	[1.77]	[1.69]	[2.39]	[2.05]
R^2	0.484	0.496	0.567	0.588	0.592
Adjusted R^2	0.484	0.489	0.507	0.490	0.467
Firm Controls	No	Yes	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	--	--
Industry & City F.E.	No	No	Yes	--	--
Industry-Year F.E.	No	No	No	Yes	--
City-Year F.E.	No	No	No	Yes	--
Industry-Year-City F.E.	No	No	No	No	Yes
Number of Obs.	2,800	2,800	2,800	2,800	2,800

Internet Appendix Table 1
Robustness Test: Using Four Digit NAICS Code for Fixed Effects

This table reports regression analysis of the effect of win rate in H-1B visa lotteries on subsequent funding outcomes controlling for occupation-year fixed effects. The dependent variable in Panel A is an indicator for whether the firm receives subsequent funding in the three years following the lottery. The dependent variable in Panel B is an indicator for whether the firm goes public in the three years following the lottery. The dependent variable in Panel C is an indicator for whether the firm goes public or is acquired for at least $25 million in the three years following the lottery. The main independent variable is *Win Rate*, which is the number of H-1B visas a firm wins through the lotteries in a year divided by the number of applicants. In this table, the Industry fixed effect is based on four-digit NAICS code, otherwise the specifications are similar to those reported in Tables 2 and 3. All columns include the following firm controls: log($ amount raised previously), log(months since first round), log(months since last round), log(number of H-1B applications), log($ salary for H-1B position), and fixed effects for the number of rounds of prior financing and for the type of prior financing. Numbers in square brackets are *t*-statistics based on standard errors clustered by firm.

Panel A: Firm Receives Additional Venture Capital Funding in Next Three Years			
Win Rate	16.693 ***	20.182 ***	20.390 ***
	[7.17]	[7.08]	[5.66]
Firm Controls	Yes	Yes	Yes
Year F.E.	Yes	--	--
Industry & City F.E.	Yes	--	--
Industry-Year F.E.	No	Yes	--
City-Year F.E.	No	Yes	--
Industry-Year-City F.E.	No	No	Yes
R^2	0.314	0.375	0.384
Adjusted R^2	0.198	0.175	0.151
Number of Obs.	2,800	2,800	2,800

Panel B: Firm has IPO in Next Three Years			
Win Rate	3.708 ***	3.697 ***	3.999 **
	[3.43]	[2.77]	[2.42]
Firm Controls	Yes	Yes	Yes
Year F.E.	Yes	--	--
Industry & City F.E.	Yes	--	--
Industry-Year F.E.	No	Yes	--
City-Year F.E.	No	Yes	--
Industry-Year-City F.E.	No	No	Yes
R^2	0.206	0.290	0.324
Adjusted R^2	0.071	0.063	0.068
Number of Obs.	2,800	2,800	2,800
Panel C: Successful Exit			
Win Rate	4.574 ***	4.716 ***	4.270 *
	[3.01]	[2.61]	[1.96]
Firm Controls	Yes	Yes	Yes
Year F.E.	Yes	--	--
Industry & City F.E.	Yes	--	--
Industry-Year F.E.	No	Yes	--
City-Year F.E.	No	Yes	--
Industry-Year-City F.E.	No	No	Yes
R^2	0.253	0.313	0.339
Adjusted R^2	0.127	0.093	0.089
Number of Obs.	2,800	2,800	2,800

Internet Appendix Table 2
Patents Results Using Only Data from the 2008 and 2009 Fiscal Years

This table reports regression analysis of the effect of win rate in H-1B visa lotteries on patenting outcomes. In this table, the sample includes only observations for the 2008 and 2009 government fiscal year visa lotteries. For Panels A through E the dependent variable are, respectively: *Any Patent*, log(1 + *Number of Patents*), log(1 + *Adjusted Number of Patents*), log(1 + *Number of Adjusted Citations*), and log(1 + *Average Number of Adjusted Citations*). All dependent variables are measured over the three years following the lottery. The main independent variable is *Win Rate*, which is the number of H-1B visas a firm wins through the lotteries in a year divided by the number of applicants. Columns 2 through 5 include the following firm controls: log($ amount raised previously), log(months since first round), log(months since last round), log(number of H-1B applications), log($ salary for H-1B position), and fixed effects for the number of rounds of prior financing and for the type of prior financing. All columns include the patent activity of the firm over the three years prior to the lottery as a control (i.e., a lag of the dependent variable as defined in that specification), because past patenting activity is a strong predictor of future activity. Numbers in square brackets are *t*-statistics based on standard errors clustered by firm.

Panel A: Any Patents					
Win Rate	0.092 ***	0.086 ***	0.090 **	0.111 **	0.091
	[2.72]	[2.62]	[2.25]	[2.23]	[1.53]
R^2	0.307	0.333	0.484	0.445	0.469
Adjusted R^2	0.306	0.311	0.342	0.254	0.257
Panel B: ln(1 + number of patents)					
Win Rate	0.254 ***	0.252 ***	0.302 ***	0.398 ***	0.349 ***
	[3.59]	[3.68]	[3.63]	[3.84]	[3.01]
R^2	0.588	0.608	0.699	0.660	0.674
Adjusted R^2	0.587	0.596	0.616	0.542	0.543
Industry & City F.E.	No	No	Yes	--	--
Industry-Year F.E.	No	No	No	Yes	--
City-Year F.E.	No	No	No	Yes	--
Industry-Year-City F.E.	No	No	No	No	Yes
Number of Obs.	923	923	923	923	923

Panel C: ln(1 + adjusted number of patents)					
Win Rate	0.141 ***	0.141 ***	0.173 ***	0.231 ***	0.208 ***
	[3.75]	[3.81]	[3.94]	[4.21]	[3.51]
R^2	0.650	0.668	0.733	0.682	0.694
Adjusted R^2	0.650	0.658	0.660	0.572	0.572
Firm Controls	No	Yes	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	--	--
Panel D: ln(1 + number of adjusted citations)					
Win Rate	0.153 **	0.160 **	0.248 ***	0.343 ***	0.318 ***
	[2.35]	[2.48]	[3.07]	[3.50]	[2.92]
R^2	0.591	0.613	0.702	0.667	0.694
Adjusted R^2	0.590	0.601	0.620	0.552	0.571
Panel E: ln(1 + average number of adjusted citations)					
Win Rate	0.016	0.018	0.040	0.050	0.043
	[0.67]	[0.76]	[1.33]	[1.32]	[0.95]
R^2	0.470	0.487	0.620	0.591	0.609
Adjusted R^2	0.469	0.470	0.515	0.450	0.453
Firm Controls	No	Yes	Yes	Yes	Yes
Year F.E.	No	Yes	Yes	--	--
Industry & City F.E.	No	No	Yes	--	--
Industry-Year F.E.	No	No	No	Yes	--
City-Year F.E.	No	No	No	Yes	--
Industry-Year-City F.E.	No	No	No	No	Yes
Number of Obs.	923	923	923	923	923

Internet Appendix Table 3
Occupation Codes and Whether Applicants have a Graduate Degree

This table reports regression analysis of the proportion of variation in H-1B applicants' education that is explained by various fixed effects. The dependent variable is an indicator equal to one for prevailing wage determination (PWD) filings in which the H-1B visa applicant has a masters degree, Ph.D., or other graduate professional degree. Occupation-Year fixed effects are based on Standard Occupational Classification (SOC) codes. The PWD filings include only H-1B visa related filings, and university, hospital, and research institution filings are excluded. We also exclude all filings for which the SOC code indicates the position is for a medical doctor or dentist. Numbers in square brackets are *t*-statistics based on standard errors clustered by firm.

R^2	0.222	0.467	0.586	0.527	0.635
Adjusted R^2	0.176	0.283	0.390	0.358	0.458
Occupation-Year F.E.	Yes	No	Yes	No	Yes
Industry-Year F.E.	No	Yes	Yes	--	--
City-Year F.E.	No	Yes	Yes	--	--
Industry-Year-City F.E.	No	No	No	Yes	Yes
Number of Obs.	2,047	2,047	2,047	2,047	2,047