Human Capital, Skilled Immigrants, and Innovation

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Abstract

Before 2004, by sourcing skilled labor in the international labor market, large, innovative U.S. firms effectively utilized an alternative to investing in the existing human capital stock of these firms. After the immigration policy shock of 2004, when new skilled immigrant hiring became constrained, the firms dependent on skilled immigrant workers reduced R&D investment proactively and contemporaneously. Firm-level innovation outcome, measured by patents and citations, declined for these firms and there was an increase in Sales, General, and Administrative (SG&A) expense beginning three years after the shock. An increase in SG&A suggests a plausible increase in investment in the human capital of existing employees. Our results are robust to placebo tests, tests for alternative hypotheses, a set of falsification tests, and a battery of robustness checks. Although real wages declined for both immigrants and host-country workers after the shock, the decline is statistically significant only for the immigrant workers.

Keywords: human capital, investment, patent, R&D, skilled immigration

JEL Category: G31, J24, J61, O31, O32

What choices do firms make regarding investment in human capital? A large financial economics literature exists on optimal resource allocation and investments in physical assets, but research on corporate investment in human capital is scant.[2] [3] We provide evidence from a performance-on-structure experiment, where performance is measured by innovation outcomes and structure is defined as corporate investment policy, specifically, how firms acquire, assess, and retain human capital. We use patents, patents normalized by R&D expenditures, patent citations, and citations per patent to measure innovation outcomes. We focus on outcome to get around the difficulty of measuring human capital directly. A firm's investment policy determines 1) how a firm allocates resources to obtain human capital from the domestic and international labor market or to develop the human capital of existing employees and 2) how it adjusts capital investment in innovation to match the available skilled labor.

We focus on outcomes for firms that rely on highly skilled employees as labor inputs to innovation. First, the available data make it possible to observe the level and quality of innovation at the firm level. Second, by moving away from aggregate or industry-level human capital, measured by aggregate labor income, frequently used in the asset pricing literature, we can establish a more direct link between innovation outcomes and policy for intangible investment at the firm level. More specifically, we focus on the innovative abilities of skilled immigrants authorized to work in the U.S. on H-1B visas and the innovation outcomes of the firms that rely on the human capital of such workers. Hiring skilled immigrant workers is expensive not only because of the direct costs associated with H-1B visa processing, but also because of the indirect costs, such as advertising, administrative, documentation, legal, and political cost,

[2] For average households, human capital is the largest source of wealth prior to retirement; it contributes to 48% of the household portfolio (Heaton and Lucas (2000)) compared to 13% contribution from financial assets. Consequently, asset pricing and the investment literature has taken an early interest in the role of human capital in portfolio allocation decisions, established a link between human capital and equity return, and measured risk premia in the presence of non-tradable human capital (for e.g. Campbell (1996), Davis and Willen (2000), Degeorge et al. (2004), Lustig and Nieuwerburgh (2008), Munk and Sørensen (2010), Betermier et al. (2012), Garleanu et al. (2012), Eiling (2013), and Calvet and Sodini (2014)).

[3] Analyzing human capital investment choices at the firm level is inherently challenging because there is no framework for determining what skillsets employers need and how those requirements change with time (and the evolution of technology), and the difficulty of mapping the activities and tasks valued by employers to the skills needed to perform those tasks (Autor and Handel (2013)).

and the opportunity cost associated with delays in hiring.[4] Hence the policy choice made by some U.S. firms to hire skilled immigrant workers allows us to analyze the effectiveness of acquiring human capital (in the international market) as an alternative to making direct investments, e.g., investments in job-specific education and training in the existing human capital stock of the firm and the host-country.

Our experimental set-up mitigates the organizational underinvestment problem in the talent search process articulated by Tervio (2008), who argues that many firms underinvest in the human capital – or talent – search process and bid excessively from the incumbent (existing) talent pool, which results in higher talent rents, a reduction in the average level of talent, a low output level, and higher wage disparities. This is because the quality of human capital, or talent, cannot always be precisely assessed before a worker is hired, and can often be determined only by observing the employee on the job. Once high-quality human capital, or talent, is revealed on the job, it is not tied exclusively to the employer that has made an early investment in the talent discovery process. Many employers of H-1B workers self-declare themselves to be dependent on these workers and the lack of portability of H-1B visas implies that many of these immigrant employees are also dependent on their employers for a specific period.[5]

Our identification strategy relies on a quasi-random assignment and exploits a change in immigration policy that created a regulation-induced negative – and plausibly exogenous – supply shock in the non-incumbent H-1B worker pool. Incumbent H-1B workers are those that are currently working in the U.S. on these visa. Beginning in 2004, the shock was induced by a reduction in the quota, or number, of H-1B petitions approved in a given year. The change in immigration policy resulted in a decline in the number of petitions approved for hiring non-incumbent skilled immigrant workers from approximately 195,000 in 2003 to 90,000 in 2004.

[4] Advertising costs are incurred because of the regulatory requirement to advertise a job opening in multiple outlets to ensure that host-country workers are aware of the employment opportunity and that the employer made efforts but could not fill the position with a qualified host-country worker before considering immigrants.

[5] During the period of our study, H-1B work authorization was not portable and was granted exclusively to the petitioning employer. If an employee wanted to pursue a subsequent employment opportunity at a different organization, the new employer had to go through a new H-1B petition process.

We compare the intertemporal change in innovation for H-1B-dependent firms relative to such change in a control group of non-immigrant-dependent firms from the same industry. Specifically, we use a difference-in-difference estimate, which measures the impact of non-incumbent skilled immigrants on the change in innovation outcomes, including quality of innovation, for the immigrant-dependent firms, after the policy shock, relative to those for the control group, which provides the necessary counterfactual. One could argue that firms endogenously select whether to hire skilled immigrant workers or to become dependent on them. To alleviate this concern, we use a propensity score matched sample of control firms that are similar to our treatment firms in industry classification, size (total asset), financial risk (leverage), operational efficiency and organizational capital (SG&A), asset specificity (market-to-book ratio), research intensity (R&D expense), and innovation outcome (patent/R&D).[6] Our dynamic regression design offers a placebo test. We also analyze the managerial response to the policy shock by measuring the impact on R&D investment, firm-level change in employment, and plausible increase in investment in education and training of existing employees. The last offers a test for an alternative channel to investment in human capital. As a falsification test, we measure the product market-, operational-, and capital market-performance around the policy shock. We test for various alternative hypotheses as part of the core set of tests or as robustness checks.

Human capital of employees not in leadership roles (e.g. skilled workers or Ph.D. scientists) but those engaged in innovative activities, and major factors that motivate or hinder their productivity have not been analyzed in great details in the financial economics literature. Among the exceptions are work on direct employee incentives (Azoulay et al. (2011), Ederer and Manso (2013), Chang et al. (2015), Hvide and Jones (2016)), tolerance for failure (Azoulay et al. (2011), Manso (2011), Ederer and Manso (2013), Tian and Wang (2014)), and indirect employee (dis)incentives from bankruptcy code (Acharya and Subramanian (2009)) as well as labor law and unionization (Acharya et al. (2014), Bradley et al.

[6] SG&A is a measure of organizational capital (Li et al. (forthcoming))

(forthcoming)), among others.[7] Our research question is significantly different from the four studies most closely related to ours. Acharya and Subramanian (2009) find that a creditor-friendly (and less failure tolerant) bankruptcy code reduces firm level innovation and Acharya et al. (2014) find that laws that protect employees against unjust termination of employment help innovation and the creation of new firms. Chang et al. (2015) find that non-executive employee stock options, especially those targeted at innovative employees, have a positive impact on innovation and Bradley et al. (forthcoming) find that a passage of union election results in a decline in innovation.

Firms make strategic choices regarding in-house development vs. acquisition of human capital and innovation output. Bena and Li (2014) provide evidence that nature of investment in innovation and innovation output determines whether a firm becomes a target or an acquirer. Lee et al. (2017) show the importance of human capital proximity in mergers and acquisitions decisions.[8] We are the only ones, except Lee et al. (2017), to our knowledge, to provide a comprehensive firm-level analysis of human capital investment/acquisition policy, and the only ones to specifically analyze the policy to source human capital from the international market, and the effectiveness of the policy, for large R&D-intensive firms that are predominantly in manufacturing industries. We are the only ones to assess the impact of the human capital investment policy choice on the quality of innovation for the immigrant-dependent firms and the capital market reaction to this policy choice. Although there is a large literature on the effect of specific immigration policies on various outcomes, including innovation, for the host-country, this study is one of the few to use quasi-random or random assignment.[9] Even fewer provide a firm-level analysis.[10] We find

[7] We leave out an extensive literature on CEO and/or entrepreneur or venture capitalist human capital for brevity.
[8] Hennessy and Lidvan (2009) analyze the impact of a firm's capital structure (and financial distress risk) on intangible human capital of an employee agent (Edmans (2011) establishes a relation between well preserved human capital and long-term capital market performance.
[9] To our knowledge, the only other works that exploit quasi-random or random assignment to estimate the impact of immigrants on the host-country economy are Edin et al. (2003), Åslund et al. (2011), Peri et al. (2015b), Doran et al. (2016), and Ghosh et al. (2016).
[10] To our knowledge, Kerr and Lincoln (2010), Doran et al. (2016), and Ghosh et al. (2016) are the only ones to provide firm-level analysis.

that the policy to source human capital from the international market is highly effective for our sample firms.

We provide evidence that firm-level innovation outcomes – both the level and the quality – decline when fewer skilled immigrant workers are hired by the immigrant-dependent firms. Before the 2004 immigration policy shock, for every million U.S. dollars spent in research and development (R&D), firms dependent on H-1B workers had twice as many patents than the non-dependent firms. By 2009, after four years of immigration policy–induced decline in the supply of H-1B workers, immigrant dependent and non-dependent firms had a similar number of patents for every million U.S. dollars invested in R&D. For the immigrant dependent firms, we observe a 20%–51% decline in patents each year beginning with the fourth year after the immigration policy shock. Before 2004, patents from the firms dependent on H-1B workers generated 65% more downstream citations as the patents from non-dependent firms. By 2009, patents from the dependent and non-dependent firms had a similar number of citations. For the immigrant dependent firms, we also observe a 44%–62% decline in citations each year beginning with the fourth year after the immigration policy shock and a 16%–29% decline in citations per patent after the shock. Beginning the third year after the shock, H-1B dependent firms start making 10% to 20% higher level of investment (relative to the control group) in Sales, General, and Administrative (SG&A) expense, which would include incremental investment in current employee education and training, the alternative channel to invest in existing human capital stock.

We find no evidence of the alternative hypothesis of "it's hard work and employee exploitation" and not skill that motivates firms to hire H-1B workers. The policy shock does not affect the firm's product market performance or profitability. We also provide evidence against the hypothesis that skilled immigrant workers displace or substitute for similarly qualified host-country workers. When fewer immigrant workers are hired, we observe a preemptive reduction of investment in R&D and an immediate 7% - 8% decline in the firm-level employment in the year of the immigration policy shock and the year after for the immigrant dependent firms relative to the control group. Thus, we add to the unresolved debate on the “crowing-out” effect in the immigration and labor literature by providing evidence against the broad claim that skilled immigrants displace or substitute for similarly qualified host-country workers. Our evidence suggests that crowding out of host-country workers is less likely to happen in firms that are similar to the ones in our sample: larger, more innovative firms with a high level of patenting, and that are in R&D-intensive and manufacturing industries. In general, employers respond to a negative shock to the supply of skilled immigrant workers by retaining more of their existing skilled immigrant workers. While the H-1B dependent firms in our sample experience a decline in innovation after a policy shock, these firms are not penalized by the capital market.

Real wages have declined for both the immigrant and host-country workers after the immigration policy shock. We observe a statistically insignificant 1.6% decline in prevailing real wages in the host country for similar workers, and a statistically significant 2.3% decline in real wages for the immigrant workers after the shock. We also find a statistically insignificant 7.2% decline in the real wage premium over the prevailing real wages paid to immigrant workers after the policy shock. Thus, we also provide evidence against the claim that skilled immigrants depress the prevailing wages of the host-country workers. These results are almost identical even if we exclude observations from the period of the economic crisis of 2008-2009.

Our work has implications for the current debate on immigration policy. Our findings complement and significantly add to the results reported by Kerr and Lincoln (2010), Hunt (2011), and Peri et al. (2015a, 2015b) that, in general, skilled immigrants add value to the host-country economy. The demand side, specifically a for-profit organization, does not appear as a unit of economic analysis in these studies except in a very limited way (one Table) in Kerr and Lincoln (2010), and even then it’s a passive entity. We provide new results on the quality of innovation outcomes and how firms respond to an immigration policy shock: by adjusting R&D investment, by reducing overall employment at the firm level, and by increasing SG&A expenditure. The lack of any capital market reaction to the policy choices made by the immigrant-dependent firms suggests that the market believes that the firm-level policy adjustments have been appropriate. Our results contradict those of Doran et al. (2016), who find that skilled immigrants displace host-country workers and have no or very little impact on firm-level innovation. We provide explanations for these contradictory findings and reconcile these two different sets of results in the Internet Appendix at the end of this paper. This work complements the analyses by Hunt (2011) that U.S. firms (along with U.S. universities and teaching hospitals) are among the most successful in selecting immigrants who engage in activities that increase the total factor productivity in the U.S. Unlike Hunt (2011), who concludes that the institutions mentioned above identify immigrants based primarily on education level rather than on superior innovative abilities, we demonstrate that U.S. firms are able to select workers with superior innovative abilities from a labor pool with a very similar education level.

2. Data, Sample Selection, and Descriptive Statistics for Skilled Immigrant Workers

We use five primary sources of data: i) United States Citizenship and Immigration Services (USCIS) for characteristics of specialty occupation workers; ii) Department of Labor (DOL) for data on Labor Condition Application (LCA); iii) United States Patent and Trademark Office (USPTO) for patents and citations data; iv) Compustat for firm-level accounting and financial information; and v) CRSP for security prices and return for our sample firms.[11] Our core LCA data are from 2002 to 2011, and patent data are from 1995 to 2010.

2.1. H-1B Quotas and Petitions to USCIS

A significant number of recent legal immigrants in the U.S. are highly skilled. They come under the H-1B visa program governed by the Immigration and Nationality Act (INA), section 101 (a) (15) (H), which allows U.S. employers to employ skilled temporary foreign workers in "specialty occupations."[12] A U.S. employer must file an H-1B petition with the U.S. Citizenship and Immigration Services (USCIS) before

[11] We use the patents and citations database from Kogan et al. (2017) made available by Noah Stoffman.

[12] A specialty occupation is defined as "an occupation that requires theoretical and practical application of a body of highly specialized knowledge in a field of human endeavor including but not limited to architecture, engineering, mathematics, physical sciences, social sciences, biotechnology, medicine and health, education, law, accounting, business specialties, theology, and the arts." The initial length of employment can be for up to three years, with a possibility of extension for another three years.

employing a temporary H-1B worker. USCIS evaluates the applicant's qualifications and approves or rejects the petition. Petitions for continuing employment are filed for foreign workers who are already in the U.S. and refer to extensions, sequential employment, and concurrent employment.[13] For each year, the maximum number of petitions approved for initial employment is subject to a cap or quota. The H-1B quota for any given year applies to the fiscal year (FY) beginning October 1 of the previous calendar year. Employers can start filing H-1B visa applications with the USCIS for prospective H-1B workers beginning on April 1 until the quota has been filled for the upcoming fiscal year. For example, for the FY 2011 beginning on October 1, 2010, the USCIS started accepting petitions on April 1, 2010.

In the early 1990s petitions rarely reached the cap and until 1997, the annual cap was 90,000 workers. In the mid-1990s, a large number of petitions used to be denied once the quota has been reached each year. The annual cap was increased to 115,000 workers in 1999 and 2000 and to 195,000 from 2001 to 2003 under the American Competitiveness and Workforce Improvement Act (ACWIA) of 1998. In 2004, upon expiration of the temporary increase, the cap reverted to 90,000. Since 2006, the basic quota has been 65,000, with an additional 20,000 exemptions for foreign workers with master's or higher degrees from U.S. universities. The H-1B cap or quota applies only to petitions for initial employment filed for first-time H-1B workers working for a for-profit organizations.[14] Petitions for continued employment with the same employer are not subject to quota. Transfers among employers count toward the quota only when an H-1B worker moves from a job with an employer that is exempt from the quota to a non-exempt employer. For each FY, USCIS provides the characteristics of specialty occupation workers, associated industry categories based on the North American Industry Classification System (NAICS), and the number of petitions received and approved for initial and continuing workers.[15]

[13] Extensions refer to petitions for H-1B workers to extend their work beyond the initial thee-year period for a total of up to six years. Petitions for sequential employment are filed for workers transferring among H-1B employers within the six-year period. Concurrent employment petitions refer to filings for H-1B workers who intend to work simultaneously for a second employer.

[14] A foreign worker is exempt from the cap if she is employed at an institution of higher education, an affiliated nonprofit organization, or a non-profit research or government organization. Petitions for moving from one non-exempt H-1B employer to another are not subject to the quota.

[15] U.S. Citizenship and Immigration Services (http://www.uscis.gov/tools/reports-studies/reports-and-studies).

2.2. Matching Compustat Firms to Firms Filing a Labor Condition Application (LCA)

Before filing an H-1B petition with USCIS, a U.S. employer must file a Labor Condition Application (LCA) with the Department of Labor (DOL). To obtain approval from the DOL, a U.S. employer must advertise the opening in multiple outlets, demonstrate that the position normally requires at least a U.S. bachelor's degree or its foreign equivalent in a specific field, and provide evidence that the foreign worker is offered the prevailing wage.[16] Once DOL approves the LCA, the U.S. employer can then file the H-1B petition with USCIS. The LCA files include the following (and other) information: filing date; name of the company filing the H-1B petition; location of the employer (state, city, postal code, address); length of the employment (beginning and end date); job title and code; approval status (certified or denied); and location of employment.[17]

We compile the LCA data for the period 2002 to 2011 from the OFLC website, a total of 2,952,791 H-1B LCAs. For each LCA, we identify and categorize each job into the following five primary groups: i) Computer-related; ii) Engineering and Architecture; iii) Life Science, Social Science, and Mathematics; iv) Administrative; and v) Education, Law, Arts and Entertainment. Since there is no unique company identifier in the LCA, we identify each firm by its name. We have a total 774,786 firm-year observations for the period 2002–2011 in the LCA dataset. We discard the employers that do not have at least 20 LCAs in one of these years. We choose 20 because using a lower number, such as 10 or 5, dramatically increases the number of sample firms and it becomes much more difficult to get a high-quality match for the control group of non-dependent firms.

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[16] "The Immigration and Nationality Act (INA) requires that the hiring of a foreign worker will not adversely affect the wages and working conditions of U.S. workers comparably employed. To comply with the statute, the Department's regulations require that the wages offered to a foreign worker must be the prevailing wage rate for the occupational classification in the area of employment. The prevailing wage rate is defined as the average wage paid to similarly employed workers in a specific occupation in the area of intended employment."

[17] LCA data beginning in 2008 can be accessed at: http://www.foreignlaborcert.doleta.gov/performancedata.cfm. Archived data for years prior to 2008 can be accessed at: http://www.flcdatacenter.com/CaseH1B.aspx.

With this filter, we obtain 18,693 firm-year observations. Next, we match the firms in the LCA dataset with Compustat firms by firm name. Firm names in the LCA dataset, however, are not unique. For example, LCA filings report Apple Inc. as "APPLE COMPUTER INC.," "APPLE INC," and other variations of APPLE names in combination of lower-case and capital letters. We apply a string matching procedure that compares two strings for the unique part of the firm name – one in the LCA database and the other in Compustat. We set the matching threshold to be at least 70% and emphasizing a more stringent matching criteria at the front end of the string.[18] Initially we obtain 3,474 firm-year observations matched to Compustat. Subsequently, we manually check for variations in firm names to modify our matching algorithm. If there is a doubt, we check the company profile and SEC filings to make a final determination. We also combine filings made by subsidiaries with those of the parent firms. For example, Microsoft Licensing is a subsidiary of Microsoft Corp.; however, LCA filings are made under both the Microsoft Licensing and Microsoft Corp. names. In such cases, we combine LCA filings by Microsoft Licensing with those by Microsoft Corp. With this consolidation of names, we obtain 2,861 firm-year observations with 728 unique firms associated with a total of 320,778 LCA filings for the period 2002–2011.

We classify a firm to be H-1B-dependent (treated) if it hires at least 20 H-1B employees in 2002 or 2003 (prior to policy shock in 2004) and obtain 183 such firms. Although it is possible to apply a filter for H-1B dependency based on the number of H-1B workers hired by a firm relative to the total number of employees of the firm, it should be done carefully because H-1B workers hired in each FY is a flow, while the total number of employees is a stock. On average, if each sample firm hires 20 employees each year and the attrition rate among the H-1B workers is similar to the average 3.5% attrition or "separation" rate in the U.S. workforce, then hiring 20 H-1B employees in each year during our sample period of 2002–2011 translates into an H-1B worker stock of approximately 5.5% of the total workforce for a sample firm.[19] With an average 55%–60% retention rate for each initial employment LCA cohort, the H-1B stock becomes

[18] For comparison purpose, the popular personal genomics companies call it a match at a 50% threshold.
[19] Bureau of Labor Statistics Job Opening and Labor Turnover (JOLT) archived data (http://www.bls.gov/schedule/archives/jolts_nr.htm).

approximately 3%. Hence, if one were to impose an annual filter on H-1B employee flow as a percentage of the total employee stock of a firm, it would be around 0.5% a year. We do apply this alternative threshold for H-1B dependence and discuss our findings as part of the robustness check.

We obtain financial and accounting data for the sample firms in the merged dataset from Compustat, and all variables are defined in Appendix Table A.1. We match the LCA data with firm-specific variables from Compustat for the next calendar year. For instance, FY 2002 in the LCA dataset begins on October 1, 2001, and ends on September 30, 2002. Hence LCAs from FY 2002 have been matched with Compustat calendar year 2002 data, which begins on January 1, 2002, and ends on December 31, 2002.

2.3. Investment in Innovation and Innovation Outcome

We use the research and development (R&D) expenditures of a firm as a measure of its research intensity and financial capital investment in innovation. For firms that do not report R&D expenditures we record zero expenses. For robustness, we also analyze a subsample of firms with non-zero R&D expenditures.

We measure a firm's innovation outcomes or productivity by the number of patents filed by the firm in a given year, and use the average number of citations for these patents as a measure of innovation quality. Although patents provide an imperfect measure of innovation outcomes, they are the most widely accepted empirical measure of a firm's innovation output (Griliches (1990)). Since we have patent data until 2010, both patent and citation measures are subject to truncation bias toward the end of the sample period, as patent grants lag patent applications by two years on average. Hence we decide not to use the 2010 data and the LCA-Compustat-patent merged dataset is until 2009. In addition, patents toward the end of the sample period will have relatively less time to accumulate citations. We correct for these truncation errors following Hall et al. (2001) and Seru (2014) by dividing the number of patents (citations) for each firm in a given year by the mean number of patents (citations) in that year and within the same patent technology class as defined by USPTO. Our citations measures are adjusted to account for self-citations. Following

Seru (2014), a firm-year observation with no patent (citation) is treated as having zero patents (citations). On average, a sample firm with non-zero R&D expenditures and patents has 0.19 patents (standard deviation of 0.25) for every million U.S. dollars in R&D expenditures and 0.28 citations (standard deviation of 0.44) for each patent in a given year. These statistics are consistent with the literature (Chava et al. (2015)).

3. Econometric Methodology and Identification

3.1. Propensity-Score Matched Control Sample

A firm's decision to hire H-1B employees could be endogenous in its innovation outcomes and determined by observed and unobserved firm-specific factors. Selection bias can occur because innovation outcomes in H-1B dependent firms can differ from those in non-dependent firms even in the absence of treatment (H-1B dependence) owing to both observed and unobserved factors. If firms are randomly assigned to H-1B-dependent and non-dependent status then such bias could be eliminated, which is difficult with non-experimental data.

Following Rosenbaum and Rubin (1983), we use the propensity-score matching method and the nearest-neighbor matching approach to minimize the effect of the selection bias. The propensity score measures the probability of being treated (H-1B status) given the observed characteristics. For a given propensity score, the conditional distribution of relevant observed covariates is independent of assignment into treatment. Therefore exposure to treatment (H-1B status) can be considered random for observations with the same propensity score because firms with the same score have the same distributions of observable and unobservable characteristics independent of treatment status.

We estimate propensity scores using a probit model, also used by for e.g. Chemmanur et al. (2014), where the dependent variable equals one if the firm is H-1B dependent and zero otherwise. The details of the estimation results are reported in Internet Appendix Table A.1. H-1B-dependent firms are matched with a control group in the year 2001 (in the pre-sample period) based on the propensity score measured with firm size, leverage, market-to-book ratio, sales, general, and administrative expense (SG&A), R&D expenditures, and patent/R&D as covariates within the same 4-digit SIC industries. Leverage is a measure of financial risk, market-to-book ratio is a measure of asset-specificity/growth opportunity/information asymmetry, SG&A is a measure of operational efficiency, R&D expenditures is a measure of financial capital investment in innovation, and patent/R&D is a measure of innovation outcome per unit capital investment in innovation. The propensity score is the predicted probability of being in the treatment group obtained from the probit regression for all treated (H-1B-dependent) and control (non-dependent) firms. Treatment firms are matched to control firms from a list of propensity-score matched K-nearest neighbors (K=3) with replacement. This provides us 206 control firms.

In Panel A of Table 1, we compare univariate characteristics of H-1B-dependent and non-dependent firms, before and after matching, along the dimensions on which the matching was performed, as well as for additional relevant variables. The diagnostic test results verify that means of covariates are very similar for the treated (H-1B-dependent) and the matched control (non-dependent) group of firms. We also report the standardized bias before and after the matching for each of these characteristics.

3.2. Treatment (H-1B-dependent) and Control (Non-dependent) Groups of Firm Characteristics

Panel B of Table 1 shows that at the time of matching (in 2001), the treatment (control) firms have assets of $11.6 billion ($10.0 billion), a leverage or debt-to-asset ratio of 0.17 (0.18), and a market-to-book ratio of 2.2 (1.8).[20] The p-values for the difference of mean for the two groups are 0.87 or higher for size measured by assets and for financial risk measured by leverage. The groups are also closely matched in performance. The H-1B-dependent (non-dependent) firms have an average annual revenue of $8.4 billion ($5.5 billion) and 32,300 (21,800) employees. Thus the mean size of our sample is comparable to the median in KL.[21] Our treatment and control firms are similar in terms of efficiency with respect to labor-

[20] All values reported in the paper are in 2001 US dollars, and hence real dollars.

[21] Much of this difference can be attributed to the different sample selection filter applied by KL, which has only 77 firms in the sample. These are some of the largest and most innovative firms because their threshold for both H-1B dependency and innovative

related costs of revenue generation, measured by the sales, general, and administrative expense (SG&A). The treatment (control) firms on average spend $ 1.9 billion ($1.2 billion) on SG&A and have a Tobin's-q of 3.1 (2.5). On average, the H-1B-dependent (non-dependent)) firms spend $236 million ($114 million) a year on R&D. Formal tests for the difference of means for the treatment and the control groups for firm specific characteristics such as size (assets, market value of equity, employees, revenue), labor cost (SG&A), financial risk (leverage), asset specificity (market-to-book ratio, Tobin's-q), show a p-value of 0.13 – 0.96. Hence we reject the null hypothesis that the control group of firms are not a good match for the treated firms. Pooled summary statistics for 1999-2009 are presented in Panel C of Table 1.

3.3. Difference-in-Difference Estimates

For identification, we use difference-in-difference estimates based on Ashenfelter (1978). We use our propensity-score matched untreated or control group of firms, i.e., firms not dependent on H-1B workers, to measure the impact of a decline in non-incumbent H-1B worker hiring on the innovation outcomes of H-1B-dependent firms, our treatment group. Given that the control group of firms were very similar to the firms in our treatment group in the pre-treatment period, the outcomes of the control group provide a valid counterfactual. The assumption of parallel trends between the treatment and the control group of firms in the pre-event period are generally validated in Figures 1-5. A moderate increase in patents and citations (and plausibly R&D expense) in 2000-2002 period could be attributed to the first wave of arrival of additional H-1B workers in 1999, although it's plausible that the increase is a lagged effect of the internet boom of the late 1990s (Figures 1-3). In the latter case it would likely have similar effect on both the treatment and control group if one believes in the effectiveness of our propensity score matching.

For multivariate analysis of the outcome variables in response to the regulatory shock in immigration policy, we use the following specification:

ability, measured by the number of patents in a given year, is much higher than ours. The median (average) firm in KL has $ 9.5 billion ($22.5 billion) in revenue and 37,000 (65,000) employees.

$$y_{it} = \alpha_0 + \mu_i + \tau_t + \beta \cdot 1_{H1B-Dependent} \cdot 1_{post} + \delta \cdot \boldsymbol{X}'_{it} + \varepsilon_{it} \qquad (1)$$

In our specification, y_{it} is the level of outcome variables for firm i in year t, such as financial capital investments in innovation measured by R&D expenditure, level of innovation output measured by patents, and quality of innovations by number of citations. The terms μ_i and τ_t represent the firm- and year-fixed effects for firm i and year t, respectively. Similar specifications have been used in prior literature (e.g. Banerjee, Gertler, and Ghatak (2002) and Ahern and Dittmar (2012)). As a benchmark or reference, we also measure the impact of a decline in H-1B worker hiring on an H-1B- dependent firm's product market output measured by revenue generated, size of workforce measured by number of employees, profitability measured by ROA, investment in current employee education and training proxied by SG&A, and capital market reaction measured by raw and market-adjusted return. $\boldsymbol{X}'_{it}$ is a vector of relevant control variables. $1_{H1B-Dependent}$ is a binary variable that takes the value of 1 if the firm is dependent on H-1B employees, and 0 otherwise. 1_{post} is an indicator variable that takes the value of 1 in the period after the immigration policy shock (year = 2004 and later). Hence, the parameters of interest are β, which provide the mean shift in innovation for H-1B-dependent firms relative to the non-dependent firms after the immigration policy change after controlling for other factors. Standard errors are clustered at the firm level.

If the policy choice to acquire skilled immigrant human capital is more effective than investing in the existing host-country human capital stock, after the immigration policy shock, we expect to observe a decline in the level and quality of innovation outcomes for the firms dependent on skilled immigrant workers. Otherwise, we expect to observe no change, or a positive change, in the level and quality of innovation output after the shock. If the non-incumbent immigrant workers displace or substitute for host-country workers, we expect no change in firm-level employment after the policy shock, or even a positive change if the immigrant workers work more hours, relative to their host-country counterparts, to ensure job security. We expect managers to reduce R&D investment to match lower labor input. Given that the immigration policy shock is exogenous and beyond the control of the immigrant-dependent firms, we do not expect a capital market reaction to the policy shock unless the immigrant-dependent firms fail to adjust to the shock.

The standard specification presented in equation (1) assumes there is no time-series variation in the innovation outcomes subsequent to the immigration policy change, which is unlikely to be true. Following Autor (2003) and Greenstone and Hanna (2014), we use an alternative specification. This modified specification allows us to provide a placebo test and to capture the time-series evolution of the impact of the immigration policy-shock on a firm's innovation outcomes, analogous to an event study. Allowing for this evolution is important because there is a lag between the supply shock to the non-incumbent H-1B worker pool and the observed innovation outcome for the firm, i.e., filing of patents and the downstream citation of patents. Ex ante, we do not know what the lag is but expect it to be two to five years based on Acharya et al. (2014).

$$y_{it} = \alpha_0 + \mu_i + \tau_t + \sum_{n=-5}^{5} (\beta_n \cdot 1_{H1B-Dependent} \cdot 1_{post} \cdot \boldsymbol{T}_{n,it}) + \delta \cdot \boldsymbol{X}'_{it} + \varepsilon_{it} \quad (2)$$

In equation (2), the vector $\boldsymbol{T}_n$ consists of a separate indicator variable for each year beginning 1999. Here, *n* is normalized such that it equals zero in 2004, the year the new immigration policy is implemented. The coefficients of interest areβ_n, which measure the change in innovation in the year n after the immigration policy shock for firms dependent on H-1B workers relative to the firms that are not dependent on such workers.

4. Results

4.1. Descriptive Statistics for H-1B-Dependent Firms

We describe the distribution of H-1B workers hired by our immigrant-dependent and control firms along two dimensions: occupation and industry. The results are reported in Table 2. During 2002–2008, an average of about 125 H-1B-dependent firms filed petitions to hire H-1B workers but in 2009, the year of the great recession, only 41 firms filed such petitions, respectively (Panel A, Table 2). Our sample firms filed 115,000 petitions between 2002 and 2009 to hire a combined total of about 14,300 H-1B workers in a year, on average, or about 130 workers per firm, except in 2009 when the average number of petitions was only 50% of that for the rest of the years.

The demand for H-1B workers is highest in the computer-related occupations. On average, about 58% of all H-1B petitions are filed for computer-related occupations, 23% for social and life sciences, mathematics, and related occupations, and 12% for engineering- and architecture- related occupations. Engineering- and architecture-related occupations experienced a significant negative shock to the hiring of H-1B workers just before the collapse of the housing bubble. The contribution of this category to aggregate H-1B hiring declined from 22% in FY 2007 to 6% in FY 2008. Prior to the financial crisis about 6% of the petitions were filed for administrative specializations, but the number of filings for these occupations has been close to zero since 2009. Similarly, the number of H-1B petitions filed for occupations related to education, law, arts, and entertainment declined from 1.6% before the shock to 0.3% after the shock.

The distribution of sample firms across different industry groups is reported in Panel B of Table 2. Manufacturing industries (SIC code 3000–3999) contribute to the largest fraction or 37% of H1-B worker hiring. Service industries (SIC code 7000–7999), including Computer and Data Processing Services (SIC code 7370–7379), hire the second highest number of H-1B workers at 34%.[22] Industries from SIC code 2000–2999, including Chemicals and Allied Products (SIC code 2800–2899) and Petroleum and Coal Products (SIC code 2900–2999), hire the third highest number of H1-B workers at 13%. By design, we have a very similar distribution of firms across industries in the control group. Consequently, 31% of our control group firms are from the manufacturing industries, 38% are from service industries, and 15% are from industries related to intermediate or value-added processing of commodities.[23]

[22] If we define H-1B dependency based on the entire sample period instead of the pre-treatment period, these numbers become 40% and 30% respectively.
[23] In a previous draft where H-1B dependency was defined using the entire sample period, the first two numbers used to be 38% and 32% respectively.

4.2. Investment in Innovation and Outcome before the Immigration Policy Shock: Univariate Comparison of H-1B-dependent and Non-dependent Firms

Panel A of Table 3 shows that before the immigration policy shock the H-1B-dependent firms had 30 patents on average compared to the 9 patents for the control group of firms and a difference of 21 patents. [24] In the period after the shock the average number of patents for these firms became 24 and 8, respectively, and the difference narrowed to 16 patents. Thus, the difference-in-difference in the number of patents before and after the shock is 5 patents and is statistically significant. These trends are shown in Figure 1. The outcomes are even starker if we consider the results presented with a three year lead. With a three year lead the difference-in-difference is 10 patents. This is because it might take three years from the time of hiring of an employee to the time when the outcome of innovation from that employee is patented and an equivalent amount of time for the impact of policy shock to reflect on the innovation outcome.

Before the immigration policy change, the H-1B-dependent firms have 27 downstream citations each year, on average, compared to 9 citations for the non-dependent firms (Panel A Table 3), with a difference of 18. The trends are shown in Figure 2. After the policy shock, the average number of citations for these two groups are 16 and 5 respectively and the difference narrows to 11. Thus the difference-in-difference is 7 citations and is statistically significant. With a three year lead, the difference-in-difference is 13. Although it might be tempting to conjecture that the decline in innovation outcome measured by citations for the non-dependent firms is due to knowledge spillover, or lack thereof, from the H-1B dependent firms to non-dependent firms after the immigration policy shock, due to limitations in our dataset, we are not able to test for such an effect.

Before the immigration policy shock, H-1B-dependent (treatment) and non-dependent (control) firms invested $215 and $ 108 million, in 2001 dollars, respectively, on innovation, measured by R&D expenditure, as shown in Panel B of Table 3.[25] Figure 3A shows the trend in average research and

[24] The median (average) firm in Kerr and Lincoln (2010) has 167 (345) patents per year.
[25] The median (average) spending by a firm in the sample used by Kerr and Lincoln (2010) is $519 million ($1.224 billion) per year (nominal dollars) between 1995 and 2007. We select a much broader sample to demonstrate that the impact of immigration policy on innovation is not restricted to the largest or the most innovative H-1B-dependent firms, and is much more widespread.

development expenditure for the treated and the control firms and suggests that financial capital investment on innovation is not a sticky policy variable. Relative to the non-dependent firms, H-1B-dependent firms pro-actively adjusted R&D investment downward in 2003-2005 to respond to the anticipated negative supply shock to the immigrant human capital around the policy shock. Panel B of Table 3 shows that between 1999 and 2002, the immigrant dependent and control firms spent $225 and $108 million in R&D, respectively, with a difference in $117 million. Between 2003 and 2005 these firms spent $ 191 and $111, respectively on R&D, with a difference of $80 million. Thus, the difference-in-difference in the R&D expenditure in this period was -$37 million and this decline is statistically significant.

Figure 3B suggests that our treatment and control group of firms spend similar amount of money in SG&A expense. Although we see (Panel B Table 3) that the H-1B-dependent firms spend $ 670 million ($730 million) more than the non-dependent firms on SG&A before (after) the shock, the univariate difference-in-difference in spending on SG&A for these two groups of firms are observationally equivalent.

4.3. Impact of Immigration Policy Shock: H-1B Workers and Innovation - Multivariate Analysis

The effects of the immigration policy shock on innovation input and outcomes measured by patents are shown in Panel A of Table 4. On average, a 13% decline (Model 3) is observed in the number of patents after the shock, resulting in four fewer patents per firm after the shock, implying there were approximately 4,300 fewer patents for the H-1B-dependent firms between 2004 and 2009. These innovation outcomes are worse if we consider that it takes time for the effect of a hiring constraint from an immigration policy shock to show up in innovation outcomes. With a lag of two (three) years, the decline in the number of patents (Model 5 and 6) after the immigration policy shock is 39% (51%), or 11 (15) patents for each H-1B-dependent firm, i.e., approximately 12,000 to 16,000 undeveloped patents in aggregate among our sample H-1B dependent firms.

In robustness tests, we divide our sample according to each firm's H-1B dependency, and the top tercile of H-1B-dependent firms has characteristics those in Kerr and Lincoln (2010).

The total number of citations of the patents of H-1B-dependent firms declines by 19% (Model 1, Panel B of Table 4) or five fewer citations, after the immigration policy shock, relative to the non-dependent firms. If we consider the effect with a lag of two (three) years, we observe a decline of 48% (56%) or 13 (15) fewer citations each year. We also observe an average decline of 15% in citations per patent. This implies that for the immigrant-dependent firms there was a decline in both innovation quality and innovation quantity after the immigration policy shock.

In Table 5, we report the results from a subsample of firms that are most dependent on H-1B workers. Within each industry, we rank our treatment firms into three groups based on how many LCAs each firm has filed within the sample period.[26] Results for innovation outcome are economically stronger for this subsample; impact on the raw number of patents and citations per patent are higher for this group.

In Table 6, we report the results from a subsample of H-1B dependent firms that are among the most dependent on skilled workers in computer related occupation. The sample H-1B dependent firms are ranked into three groups within each industry based on LCA filings of job description related to computer occupations (e.g. Software Engineer, Programmer, Application Developer, Computer System Analyst, Application/System Architect., etc.), and the top ranked H-1B dependent firms belong to this sample. We find economically stronger results – in terms of impact on raw number of patents and citations per patent – for this group as well.

4.4. Evolution of the Impact of Policy Change on Innovation

For each year after the policy shock, the dynamic impact of the shortage of incumbent H-1B workers – due to the immigration policy shock – on innovation outcomes for their employers is presented in the left panel of Figure 6. The coefficients estimated from equation (2) and reported in Model 3 in of Table 7 are plotted against time. The innovation outcomes are normalized such that they are zero in year 2004, the year

[26] As an alternate measure we also scale the number of raw LCAs filed by the total number of employees for the firm and use this normalized number of LCAs to rank our treatment firms into three groups.

the new immigration policy was implemented. Beginning two to three years after the immigration policy shock, there is a sharp and steady decline in the number of raw patents and the number of patents normalized by R&D expenditure, for the immigrant-dependent firms relative to the control firms.[27] Corresponding Table 7 shows that the number of patents declined by 20% and 56%, respectively, in years +4, and +5, after the immigration policy shock.[28] These results contradict DGI's conclusion from their sample that there was only a modest effect on innovation outcomes.

The right panel of Figure 6 presents results when the number of patents has been normalized by the R&D expenditure (Model 4 of Table 7). The results are qualitatively similar, albeit economically much smaller (4% - 7%), when patents are normalized by R&D expenditure. Recall that H-1B dependent firms pro-actively reduced R&D expenditure beginning in 2003. Hence, the policy response by the skilled immigrant-dependent firms to reduce R&D expenditure seems to have been appropriate.

H-1B-dependent firms reduce their R&D expenditures in anticipation of the immigration policy shock beginning the year before the shock. Results from Model 1 in Panel A of Table 7 show a 42%, 42%, and 27%, decline in R&D expenditures in years -1, 0, and +1, of the policy shock. These results are consistent with those presented in Figure 3A. Although part of the reduction in R&D expenses can be explained by the lower aggregate wages paid by the H-1B-dependent firms to innovative immigrant workers for engaging in, directly supervising, or supporting, qualified research activities, it does not explain the magnitude of reduction in R&D. If the average non-incumbent H-1B worker is paid a wage of approximately 80,000 US dollars and the average H-1B-dependent firm hired 50 fewer H-1B workers in years +0, +1, +2, then the

[27] The univariate results in Figure 1 show a moderate decline in the number of patents for the control group of firms as well. This is consistent with the results in Autor et al. (2016) that between 1999 and 2007 there was an overall decline in patenting.

[28] It might be tempting to infer the existence of a pre-trend in the treatment group of firms based on Models 3 and 4 in Panel A. Anecdotal evidence based on conversations with several individuals in the Silicon Valley suggests that there was a large number of layoffs between 2000 and early 2002 after the 2000 NASDAQ crash and subsequent relocation back to the country of origin among many tech workers. Even though many of these workers had petitions for legal permanent residence pending, H-1B visa provides only a 60 day grace period for the workers to find another "comparable" employment and the new employer has to be willing to sponsor the worker's petition and pay a premium for expedited processing. In addition, the coefficients for these years are not stable. In a previous draft of the paper where we defined H-1B dependency based on the entire sample period of 2002-2009 and not based on 2002-2003 pre-treatment period, we found a small trend in the opposite direction, i.e. a positive effect in 2003 and 2004. At that time we believed that those positive effects are an outcome of the increase in the H-1B cap in the year 2000 visible with a three to four-year lag but that does not seem to be the case in this sample.

lower R&D expenses resulting from the lower wages should be approximately 4 million US dollars for the H-1B-dependent firms, on average. Because the average R&D expenses for the treated (control) firms are $225 million ($108 million) per year, a $4 million reduction in the wage bill cannot explain the significant reduction of at least $51 million and $44 million in R&D expenses in years -1 and 0, respectively.

A similar effect is observed for the quality of innovation. The left panel of Figure 7 plots the coefficients from the dynamic regression results for quality of innovation after the immigration policy shock. Model 5 in Table 7 presents the relative change in the number of citations after the policy shock. We observe a decline in the number of citations by 44%, and 62% in years +4, and +5, respectively, after the policy shock. When we normalize the number of citations by patent, we observe a similar effect. The right panel of Figure 7 presents the graphical results. Corresponding Model 6 in Table 7 shows a 16% to 29% lower patent citation for each patent in years +1, to +5, respectively, after the immigration policy shock for the H-1B-dependent firms relative to the control firms. Interestingly, citations per patent has a much faster rate of adjustments than the raw patents. Our conjecture is that, similar to academic publications, when a large (small) number of individuals and groups are engaged in innovation in a related area it can generate higher (lower) citations for each work when the works are in progress. Thus, the ability of a highly productive academic science lab to continue to produce high impact work with higher number of citations on current research depends on its ability to attract or hire new post-doctoral scholars to continue to work on the existing research portfolio of the primary investigator.

Our original sample was from 1999-2009 which did not provide us an opportunity to perform an extensive placebo test. In the current version, we augment the outcome variables for our treatment and control firms with observations going back to 1995. We then use the 1995 to 2002 sample and treat 1998 as the reverse (positive) shock-year when there was a small increase in the skilled immigrant worker inflow because of an increase in H-1B quota. We observe a modest and stable increase in both the quality and quantity of innovation with a lag of one to three years (Table 8), although an argument could also be made that these increases are because of the internet boom years and not because of a higher inflow of skilled immigrant workers. Each of the years from 1996 to 1999 may also be treated as a pseudo-negative shock year where we treat as if there was a decline in skilled immigrant hiring in these years when there was none. This alleviates the concern that the negative impact on innovation outcome (Table 7) that we observe from the 2004 negative shock to skilled immigrant hiring is random.

4.5. Channels Through Which Innovation Declines

Through what channels does innovation decline at the firm level? Does it decline because fewer skilled immigrant workers are hired? Or is there a decline in innovation by host-country workers as well? If fewer skilled immigrant workers are in circulation, the knowledge spillover to host-country innovators is also reduced, resulting in a decline in innovation by host-country workers.

This line of inquiry may be more relevant for geographic analysis at the city-, state-, or country- level where the executives have limited short term options and tools to manage exit or entry of human capital. Extending the same question to firm-level analysis, requires the assumption that the manager of a firm is a passive entity and is not generously compensated to respond to such contingencies and policy shocks. We discuss three different managerial responses.

In the first scenario, we have a completely non-responsive manager who keeps the number of incumbent immigrant and host-country workers and the R&D expenditure constant before and after the shock. Because of the immigration policy shock, the quantity of non-incumbent immigrant workers is lower but the talent level in this group remains constant. There will be a mechanical decline in the total number of patents by the non-incumbent immigrant workers and perhaps some additional decline due to the lack of spillover effects and a more severe decline in patents/R&D.

In the second case, we have a manager who over-adjusts her labor force but makes no adjustment to capital. While the quantity of non-incumbent immigrant workers declines, the quantity of incumbent immigrant workers increases (through more aggressive retention of the existing stock) to offset the former, and thus the total number of immigrant workers remains flat. No adjustment is made for R&D investment.

We still expect to observe a decline in the total number of patents by immigrant workers. This is because a higher retention rate for the incumbent immigrant workers results in a decline in average talent of all (incumbent + non-incumbent) immigrant workers (Tervio (2008)). Stated differently, after the policy shock, the manager is forced to retain lower-quality incumbent immigrant workers (as observed from their on-the-job performance) who would have been let go but for the supply shock to the non-incumbent immigrant workers. An artifact of this shift in retention policy is also a decline in the quality of collaboration and/or lunch/watercooler conversations resulting in poor-quality knowledge spillover. Hence there should be a sharp decline in the total number of patents, patents/R&D, and citations/patent by host-country innovators even if the total skilled immigrant worker quantity remains flat.

Finally, we have a sophisticated manager who increases the retention rate of incumbent immigrants but not to a level that completely offsets the shortage of non-incumbent workers. Instead, the manager reduces investment in R&D to match the lower labor input. We expect fewer patents but not a large decline in patents/R&D. More importantly, as the average talent declines at a slower rate than in the second case, citations/patent should decline at a moderate rate before tapering off. Figures 1, 6, and 7 are most consistent with this response by the manager.

Our data structure does not allow us to offer a second controlled experiment with quasi-randomization to test which of these responses was adopted by the managers.[29] Looking at the event-study results presented in the left panel of Figure 6, we note a decline of 20% and 60% in the raw number of patents in years +4 and +5, respectively, after the policy shock. However, when we look at the right panel of Figure 6, where

[29] In order to make a definitive statement about whether the three types of workers (non-incumbent immigrants, incumbent immigrants, and host-country workers) are substitutes or complements at the firm level, we need to be able to measure the marginal change in productivity of one factor (e.g., host-country workers) with the change in quantity of another factor (e.g., non-incumbent immigrants), holding everything else (R&D expenditures and the quantity of host-country workers) constant. This is not observed in our data. In addition, we do not know the annual in- and out-flow of each of the three types of workers for our sample firms. Finally, from the patent dataset, we can infer the ethnicity of the innovators. But we are not able to categorize the innovators as non-incumbent immigrants, incumbent immigrants, or host-country innovators of certain ethnic origin. Even for Chinese and Indian immigrants, researchers cannot tell apart the first- and second- generation innovators; and among the first-generation immigrants, it is not possible to distinguish between H-1B visa holders and permanent residents. Among the H-1B visa holders, we cannot distinguish the incumbents from the non-incumbents. Hence, we cannot provide a formal test for the role of the three channels responsible for the decline in productivity. To our knowledge, researchers using census data, e.g., from the Longitudinal Employment and Household Survey (LEHD), are not able to provide a formal test either.

the number of patents is scaled by the investment in R&D, we observe a decline of only 4% to 7% in years +2 to +5. Hence, do we really need to inform the corporate managers on which channel is responsible for a decline in innovation outcome for their firms? For immigrant-dependent firms, new knowledge about channels for the decline in innovation adds little value because the managerial response to the policy shock has been appropriate.

From the dynamic regression results presented in Models 5 and 6 of Table 7 and plotted in Figure 7, we observe that aggregate citations decline between 44% and 62% in years +4 and +5, respectively, but citations per patent decline between 16% and 19% from years +2 to +5. So, five years after the shock, there is a 19% decline in innovation quality measures by citations per patent among the immigrant-dependent firms relative to the control group of firms. An argument could be made that the change in retention policy and the greater retention of mediocre incumbent immigrants after the shock resulted in a 19% decline in talent. It could be argued that some of this decline in innovation is also the result of lower productivity among host-country workers owing to poor quality spillover. Whether poor spillover results in fewer patents or lower quality patents, or both, is beyond the scope of this study.

4.6. Alternative Hypotheses: 1) Is Hard Work a Skill and 2) Do H-1B Workers Substitute for or Complement Host-Country Workers?

In a recent op-ed New York Times op-ed piece, Senator Jeff Flake from Arizona seemed to redefine hard work as a "skill." Many would disagree. In this section we provide tests on whether the skill associated with the H-1B workers are related to their ability to work longer and harder and whether firms use H-1B hiring to exploit the host-country and immigrant employees. We expect the long or hard work to reflect in increased revenue and profitability of the immigrant dependent firms, holding all else constant. In addition, if skilled immigrants substitute host-country workers by virtue of their ability to work harder or longer than the host country workers, we should be able to observe such an effect on overall employment for the immigrant dependent firms. Figures 4 and 5 show no noticeable difference in revenue and employment growth for the treated and the control firms before and after the immigration policy shock.

In multivariate results presented in Models 1 to 4 in the Panel A of Table 9, we observe no effect on revenue or revenue normalized by asset and a negative effect on profitability – measured by ROA – of the immigrant dependent firms. In the dynamic regression results presented in Panel B of Table 9, Models 1 and 2 show a positive effect in 1999 and 2000, perhaps the tail end of the period from the tech boom. We observe a 15% - 16% decline in ROA (models 5 and 6 in Panel A of Table 9) for the H-1B dependent firms after the policy shock. In dynamic regression results (models 5 and 6 in Panel B of Table 9) we observe that most of this is driven by the large positive impact on ROA in 1999, which seems to be correlated with the positive shock to the revenue. In further robustness check, we find that this effect is primarily driven by an increase in assets and a consequent decline in contemporaneous ROA for the control group of firms rather than any major change in the treatment group.

The lack of contemporaneous direct impact of the immigration policy shock on revenue or profitability for our sample firms suggests that the value addition from H-1B workers was likely not due to any exploitation of H-1B workers by the technology service-providing firms in a sweatshop-like environment.

Immigrant-dependent firms experience a 7% - 8% decline in employment (models 7 and 8 in Panel B of Table 9) the year before the policy shock relative to the treatment group, although this effect disappears when we normalize the number of employees with assets. Similar to the decline in R&D investment, we observe a pre-emptive decline in the number of employees in the year of the shock, and to a lesser extent in the year after, relative to the control group of firms. These results provide evidence against the hypothesis that immigrant and host-country workers are substitutes and are inconsistent with the conclusion of DGI that H-1B workers displace or crowd out host-country workers. DGI find a decline in subsequent employment for firms that win the H-1B lottery, especially for smaller firms that employ fewer than 30 or fewer than 10 employees. In their research design, conditional on H-1B workers adding value through spillover effects, having won the lottery to employ additional H-1B workers is a positive shock to the firm. It should therefore have resulted in a positive or at least neutral effect on subsequent firm-level employment. In our research design, an immigration policy shock results in immigrant-dependent firms hiring fewer H-

1B workers, or a negative shock to the firm. Hence, conditional on H-1B workers adding value and not simply substituting for or crowding out host-country workers, we expected to observe a negative impact on employment after the supply shock. That is exactly what we observe.

Our earlier back of the envelop calculation that H-1B workers perhaps represent about 3% - 4% of a firm's stock of employees, and an annual flow is about 0.5% of the total employees and the stock is approximately six or more years equivalent of flow. With a 60% - 80% decline in H-1B worker flow, the one-time 7%-8% reduction in overall firm employment (holding all else constant) relative to the control group is consistent with the claims in Peri et al. (2015b) that foreign STEM workers create host country jobs and the magnitude of such employment creation.

4.7. Alternative Channels for Human Capital Access: Do Firms Increase Investment in Education and Training of Existing Employees after a Shortage of Immigrant Workers?

We do not have data of appropriate granularity to measure how much firms spend on employee education and training but the Sales, General, and Administrative (SG&A) expense would likely reflect such expenses. Hence, during a period of constrained access to human capital in the international labor market, firms will likely increase investment in education and training and such increase in employee human capital result in higher SG&A expense.

In Panel A of Table 10, we observe an 8%-9% increase in the SG&A level and 11% - 12% increase in SG&A scaled by revenue. In the dynamic regressions we continue to observe a 10% -20% positive impact on the level of SG&A two to four years after the shock. When SG&A is scaled by revenue, however, the effect disappears and seems to be driven by the increase in revenue or the relative cost-reduction from the tail end of the internet bubble. Thus, with some caveat, we may be able to argue that immigrant dependent firms might have increased the investment in existing human capital once the supply of new skilled immigrants became constrained.

4.8. Falsification Test: Impact on Other Outcome Variables including Capital Market Performance around the Policy Shock

In Table 11, we test whether our key results for innovation outcome are random and can also be observed for other outcome variables, specifically market equity, Tobin's-q, and the raw and market-adjusted return. Ex-ante, we do not expect capital markets to either reward or penalize the H-1B-dependent firms for the immigration policy shock unless the immigrant-dependent firms fail to respond to the policy shock in an appropriate way.

After the policy shock, we observe a 17% - 19% decline in market equity for the H-1B-dependent firms relative to the control firms (Model 1 and 2, Panel A of Table 11). We observe no effect on raw or and market-adjusted return (Models 5 to 8, Panel A of Table 11) or Tobin's-q (Models 3 and 4, Panel A of Table 11). Dynamic regression results (Panel B of Table 11) show that most of the impact on market equity occurred in 2004, 2005, 2007, and during the great recession years. Again, further robustness checks suggest that the number of shares outstanding significantly increased for the control group of firms in 2003, 2005, and 2006 while those for the treatment group remained stable between 2000 and 2011. This increase in the number of shares outstanding for the control group could be due to new equity issue, stock split, or both.

We observe an 18% - 20% higher raw and benchmark adjusted return for H-1B-dependent firms relative to the control group of firms in the year after the first shock. Figure 8 shows the market-adjusted returns for two equally weighted portfolios of immigrant-dependent and non-dependent firms, and these returns are observationally equivalent. After paying for a round trip transaction cost there would not have been any arbitrage opportunity.

4.9. Impact of Trade

Foley and Kerr (2013) provide evidence that when innovators of specific ethnicity contribute to a higher share of a firm's patenting activity, there is also an increase in business activities by the same firm in the innovators' country of ethnic origin. Along the same line, it could be argued that the opposite is true as well. That technology diffusion happens along with trade and any major change in trading relationship might affect innovation. We don't have firm-level import and trade imbalance data to include in our specifications. Because our treatment and control group of firms are well matched at the industry level, any industry level variation in import or trade imbalance will likely have similar effects for both group of firms. At the country level, we do observe time series change in both U.S. annual import and trade imbalance for all countries, top five trading partners, and for China and India. We include China and India separately because most of the skilled immigrant workers in the U.S. come from these two countries. In our non-parametric tests, neither the U.S. annual import from, nor the trade imbalance with these two countries are different, at the traditional level, after the immigration policy shock than before. There is some difference for the top-five trading partners; annual imports increased and the trading imbalance (negative) also increased in magnitude for the tip-five partners but not with the rest of the world.

Time series change in import and trade imbalance at the country level will be picked up by the year fixed-effects in our specifications and should not influence our results and conclusions. Regardless, we also include the country-level trade imbalance and total import in our main regression specifications and our results remain very similar both economically and statistically. These additional variables are included in separate specifications because they are highly correlated. These results are not reported for brevity.

4.10. Effect of Lobbying

Some may argue that H-1B dependent firms have to option to hire lobbyists on their behalf and because such lobbying affects how policymakers vote, the immigration policy shock could plausibly not be exogenous. This argument makes the implicit assumption that lobbying is a tool that's only available to the firms employing skilled immigrants and not to those opposed to it such as unions of technology workers, policy institutes, or wealthy individuals opposed to skilled immigration. We do acknowledge that H-1B dependent firms may have resource advantage on their side. Yet, these arguments do not negate the fact that the 2004 shock was effectively in place when American Competitiveness and Workforce Improvement Act (ACWIA) of 1998 was originally passed. Hence, this has not been corrupted by any subsequent actions that the firms might have taken. In addition, if the lobbying critique is consistently applied, then we have to cast doubt on the findings reported in a large number of published works that use passage of specific legislation as an exogenous shock. The same argument applies for use of any judicial decision because nominations and confirmations of justices might not have remained untainted by past lobbying efforts that some firms might have engaged in, firms that could benefit from subsequent judicial decisions.

4.11. What Explains the Declining Trend in Citations in 2002 and 2003

From Figure 2 we observe a sharp decline in citations for the H-1B dependent firms beginning 2002 and 2003. A similar, albeit statistically weak effect is also observed in Table 7. We spoke with several individuals with direct knowledge of the events after the NASDAQ crash of 2000 and how it might have affected innovators, especially skilled immigrants. It appears that a large number of skilled immigrants working in the Silicon Valley lost their employments in 2000 and 2001. Even though many of these skilled immigrants had their immigration petitions (for legal permanent residence), filed by their employers, under process for years (due to country of origin quota, which disproportionately affects people from China, India, and Mexico), under the H-1B policy, they had to leave the country within 60 days after termination of employment. Some of these immigrants working for larger firms were offered relocation opportunities by their employers at another country or subsidiary but many chose to go back to the country of origin. Teams were disintegrated and there was less spillover of innovative ideas. This disruptive effect is not something we can test directly with our data but is consistent with the findings of Baghai et al. (2017).

4.12. Additional Robustness

We repeat our analysis using specifications (1) and (2) only for a subsample of firms in computer-related industries (SIC code 30–39 and 73). All the results are slightly stronger for this subsample: all the coefficients are greater in magnitude, and each of the models has higher R^2 than we observe for the full sample of firms.

We also apply an alternative threshold for H-1B dependence, specifically, H-1B workers (flow) hired in a given year account for 0.5% of the total number of employees (stock). Assuming a 20% attrition rate, H-1B worker stock would account for approximately 4% of the stock of all employees over our sample period. The results remain qualitatively similar with this alternative definition of H-1B dependence. We also analyze a subsample of firms with non-zero R&D expenditures and our results remain the same.

Given that our treatment firms are smaller (much larger) and have fewer (many more) patents than those considered by Kerr and Lincoln (2010) (Doran et al. (2016)), henceforth KL (DGI), we also check for to what extent the sample distribution influences the results and conclusions. In addition to the results presented in Table 5 and discussed in section 5.3 we now split our sample into three groups based on the level of H-1B dependency, i.e., firms that hire the most, average, and least number of H-1B workers for each year and industry by SIC code. Typically, larger firms hire more H-1B workers than smaller firms. Our results are strongest for the firms that are most dependent on H-1B workers and weakest for the firms that are least dependent on H-1B workers while the results for the firms with average skilled-immigrant dependency falls in-between. Investments in innovation and innovation outcomes for the least H-1B - dependent firms resemble those of the control group of firms. The results remain qualitatively similar when we categorize our treatment firms into most- to least-immigrant-dependent firms based on the alternative definition of H-1B dependence described above. This would also explain the stark difference between the results and conclusions of KL and DGI and why our results fall in between, albeit closer to those two sets.

To protect against truncation bias in the USPTO data, we repeat our analysis with a panel of 2002–2007 data. This provides us a more balanced panel in which the number of years before and after the shock are more evenly distributed. The results remain qualitatively similar to those reported for innovation outcomes and for R&D expenditures.

In addition to matching the Compustat calendar year data to our LCA data file, we match the Compustat fiscal year (FY) data to our LCA file. Our results remain qualitatively similar in the dataset with this new matching procedure. For 87% of the Compustat firms, the FY ends between June and December, straddling the month of September, which is the FY end in the LCA dataset.

We also include an interaction term between year- and industry- fixed -effects in our specifications. Our results still remain economically and statistically significant for the quality of innovation measured by citations and citations normalized by patents. For patents and patenting intensity -- measured by patents normalized by R&D -- our results are qualitatively similar but no longer significant statistically at the traditional level.

Although it might be reasonable to ask whether the decline in innovation is caused by the smaller supply of innovators or by an increase in labor costs due to the smaller supply of innovators, the latter is a second-order effect. We are measuring the impact on innovation, not on innovation per unit of innovation-related labor costs paid in wages and benefits. It is somewhat of a stretch to argue that the labor costs of innovation increased because of an increase in labor costs for both host-country and immigrant innovators to such an extent that immigrant-dependent firms were unable to afford an adequate number of host-country and immigrant innovators to meet their needs.

Nevertheless, in Table 12 we report the wages to the immigrant workers before and after the 2004 policy shock as disclosed in the LCA filings. This also provides a test for the alternative hypothesis that the skilled immigrant workers are hired not because of their ability to innovate but because they are cheaper. Surprisingly, after the immigration policy shock, real wages declined for both the immigrant and the host-country workers. We observe a statistically insignificant 1.6% decline in prevailing real wages in the host country for similar workers, and a statistically significant 2.3% decline in real wages for immigrant workers after the shock. Before 2004, the average prevailing real wage (expressed in 2002 dollars) for the job categories in which immigrant workers were hired was $63,761, while the immigrant workers were paid $72,703 on average; in other words, a $8,906 wage premium in real dollars was paid to the immigrant worker. Beginning in 2004, the average prevailing real wage for the job categories in which the immigrant workers were hired was $62,729, and immigrant workers were paid $71,009, on average; in other words, an $8,261 or 13% wage premium was paid to the immigrant worker. There was a statistically insignificant 7.2% decline in the real wage premium over the prevailing real wage paid to the immigrant workers during this period. These results are almost identical even if we exclude the observations from the years 2008 and 2009 covering the period of the economic crisis. We find no evidence of either immigrant workers depressing wages before or becoming unaffordable after the shock.

What is the impact of the extension of Optional Practical Training (OPT), which allows international students on F-1 student visas and enrolled at U.S. universities, especially in the STEM area, to be hired by firms in the U.S.? This extension, which became effective in 2008, does not influence our results, and as such we are unable to test the impact of this policy change because our usable patent dataset is only until 2011.

5. Contribution of This Work in Relation to the Prior Literature in Labor Economics, Human Capital, and Innovation.

The two works that are closest to ours are by Kerr and Lincoln (2010) and Doran et al. (2016), henceforth KL and DGI, respectively. KL conduct what is primarily a city/geographic-level analysis of the impact of skilled immigration on innovation, but they also use firm-level analysis as a robustness check (to our knowledge, they are the earliest to introduce firm-level analysis in the immigration literature). They find that a 10% growth in H-1B worker admission is associated with a 4%-5% increase in patenting by ethnic Indian inventors working for 77 of the largest U.S. firms. In contrast, DGI find that firms that win H-1B lotteries have an economically modest and statistically insignificant effect on innovation outcomes and also conclude that firms that hire H-1B workers crowd out other workers in those firms. While our research was not originally designed to answer the question whether immigrants and host-country workers are substitutes vs. complements, given the contradictory conclusions by KL and DGI, part of our analysis can provide an out of sample test for the null hypothesis that immigrants affect host-countries through crowding-out their workers rather than through innovative abilities.

We have gone beyond the work done by KL by measuring not only the level of innovation but also the quality or impact of innovation. This is important because a small percentage of patents granted eventually results in a major innovation or contributes to future cash flow. Hence, counting only the number of patents may provide a noisy estimate of the innovation outcomes, while downstream patent citations are an important indicator of the quality and the impact of innovation (Trajtenberg, 1990). In addition: 1) we have carefully selected a propensity-score matched control sample, 2) measured the level of adjustment that firms make in R&D expenditures – the financial capital input to innovation – to match the decline in human capital, and 3) measured the product market and operational performance of and capital market reaction to the immigrant dependent firms. We also make methodological improvements in identification by exploiting an exogenous regulatory shock and quasi-random assignment instead of relying on OLS estimates, which do not address endogeneity concerns, or on 2SLS, which can provide unstable estimates and contingent on instrument validity.

DGI are able to use randomization based on H-1B lottery data from a 2006–2007 sample. Although randomization is usually preferable to the quasi-random strategy we use, in this case it comes at a cost. DGI provide results from a relatively short time series for sample firms disproportionately representing the service sector; these firms are much less innovative (with a 5%–9% patenting rate vs. 64%–85% in our sample) and much smaller in size (1,800 vs. 37,100 employees) than a typical H-1B-dependent firm. Therefore the outcomes observed in their sample firms are more likely to represent small "outsourcing" or "body-shopping" firms and less likely to represent large, innovative, and R&D intensive H-1B-dependent firms and should not be extrapolated to make a general statement about all immigrant-dependent firms that engage in innovative activities.[30] We do not observe the characteristics of the lottery-winning and -losing

[30] "Job brokers steal wages and entrap Indian tech workers in US," by Matt Smith, Jennifer Golan, and Adithya Sambamurthy for the Center for Investigative Reporting, *The Guardian*, October 28, 2014. https://www.theguardian.com/us-news/2014/oct/28/-sp-jobs-brokers-entrap-indian-tech-workers.

firms – separately – in their sample.[31] In contrast, our propensity-score matched treatment and control firms are distributionally well matched based on a series of important measures used in the corporate finance literature, thus enabling us to mitigate the concern that our results are driven by inherent differences between the treatment and control groups of firms (lottery winners and losers in case of DGI). In addition to these differences in empirical strategy, we have gone beyond DGI by providing additional results on the impact or quality of innovation measured by patent citations, by measuring the effect of the immigration policy shock on capital input to innovation, i.e., investment in R&D, and by measuring the capital market response to the labor policy choice made by the immigrant-dependent firms.

Beyond these two works, Ghosh et al. (2016) use the same exogenous shock in immigration policy that we use to estimate the impact of skilled immigrant workers on various firm-level labor productivity, size, and profitability measures. In their research design, firm size and profitability are outcomes, while we treat both to be endogenous, at least in the short-term, in a firm's research intensity and innovation outcomes. We find no difference in the impact of the immigration policy shock for the immigrant dependent and non-dependent firms for either firm size (measured by revenue, revenue normalized by asset), or profitability (measured by ROA, i.e. return on asset). The second difference is that we use patents and citations per patent as measures of innovation (outcomes) – both in level and in quality – while Ghosh et al. (2016) use R&D expenditure, which is an input to innovation, as their measure.[32] We explicitly control for R&D investment through propensity-score matched samples. Yet we find a differential impact of the policy shock on innovation outcomes for the treated and control firms. Immigrant-dependent firms respond to a supply shock in one factor for innovation (skilled immigrant labor) by reducing another (R&D investment) – something their research design is unable to capture. Although we also produce (unreported given the length of the paper but available upon request) side results regarding labor productivity and profitability per employee as Ghosh et al. (2016) do, given that immigrant workers are less than 5% of the total workforce

[31] Doran et al. (2016) provide pooled summary statistics for their sample firms and do not report the characteristics of the lottery winners vs. the rest of the H-1B firms or even the lottery losers.
[32] See Lerner and Seru (2014) for a discussion on the problems associated with using R&D expenditures as a measure of innovation.

in our (and perhaps their) sample firms, such results are inherently noisy owing to the heterogeneity of the labor, skill, and tasks associated with the input and output.

Most of the studies in the labor economics literature approach skilled immigration primarily from a regulatory policy perspective. A large proportion of the analyses are designed to test whether immigrant scientists and engineers make significant contributions directly and through spillover effects or whether they crowd out or substitute for host-country workers in their fields. Exploiting geographic variation in the level of immigration has produced conflicting results in this regard. Using state-level variation in immigration, Hunt and Gauthier-Loiselle (2010) find that college-educated immigrants encourage innovation among the host-country population. Using city- and state-level data, KL, however, find no significant effect. Using metropolitan statistical area (MSA) data, Peri et al. (2015b) conclude that each new foreign STEM worker creates between 0.5 and 0.6 host-country STEM jobs over the long term. Hunt and Gauthier-Loiselle (2010) and Peri et al. (2015b) conclude that immigrants affect U.S. innovation through positive spillover effects rather than by crowding out host-country innovators.[33] In a European study, Bosetti et al. (2015) find that when the share of skilled foreign workers in the skilled workforce increases, innovation outcomes, e.g., patent applications and citations of articles published in the scholarly literature, also increase at the national level.[34]

Peri et al. (2015a) report that foreign workers with science, technology, engineering, and math (STEM) skills increase total factor productivity in U.S. cities and that an increase in STEM workers is associated with significant wage gains for college-educated host-country workers. Kerr et al. (2015) analyze the impact of skilled immigration on the employment outcomes of workers of various skill levels and demographics, at the firm level. They conclude that increased employment of skilled immigrant workers in a firm increases

[33] The earliest recorded evidence of long-term growth and development effects in host countries resulting from the immigration of skilled human capital, technology diffusion, and knowledge spillover is attributed to the migration of the Huguenots, or French Protestant diaspora, to Prussia (Hornung (2014)).
[34] D'Amuri, Ottaviano, and Peri (2010) find insignificant adverse effects of immigration on host-country wages and employment and significant effects on “old” immigrants for German workers with no vocational, vocational, or higher education.

employment of young skilled host-country workers but reduces employment of older skilled workers.[35] Kerr and Kerr (2013) find that during a period of high inflow of immigrant workers it takes longer for STEM workers to find a new job and that their wages decline after the transition.

In addition to our other contributions, we provide new evidence on this debate by providing results on the retention policy for existing immigrant workers and hiring policy for all – host-country and immigrant – workers adopted by the immigrant-dependent firms. We find no evidence of the substitution or the crowing-out effect. Given the availability of skilled workers in the international labor market, firms in equilibrium will hire these workers for specific jobs where they have a comparative advantage (e.g., programming, research), while host-country workers will specialize where they have a comparative advantage, such as communication, design, development, and management (Ottaviano et al. (2013)). Whether hiring H-1B workers can have a long-term impact on the supply side of human capital (i.e., on the future workforce) with regards to its choices regarding investments in education (e.g., avoiding science, technology, engineering, and math (STEM) specialization) is beyond the scope of this work.[36]

A sizable body of work exists in the financial economics literature, especially firm-level empirical analysis focusing on the impact of various factors on corporate innovation and investment in innovation.[37] Among these are access to credit, financing policy, and the role of capital providers (Fulghieri and Sevilir (2009), Amore et al. (2013), Chemmanur et al. (2014), Bernstein (2015), Atanassov (2016), Chava et al. (2015)), organizational structure (Seru (2014) and the nature of a firm (Ferreira et al. (2014), Gao et al. (forthcoming)), product market relationship (Chu et al. (forthcoming)), risk and organizational uncertainty (Caggese (2012)), corporate governance (Balsmeier et al. (2017), mergers (Fulghieri and Sevilir (2011),

[35] Moser et al. (2014) analyze the effect of Austrian and German Jewish émigrés on U.S. innovation. The authors compare the time-series changes in patenting by U.S. inventors in specific fields of chemistry pioneered by Austro-German immigrants who arrived in the U.S. shortly before or during World War II with those in other fields of chemistry by non-émigré Austro-German chemists. Patenting by U.S. inventors increased significantly in the émigré field. Émigrés encouraged innovation by attracting new researchers in their fields, not by increasing the productivity of the incumbent inventors.

[36] We do recognize, however, that any decision by the supply side of the future domestic labor force to avoid investing in specific education programs, such as STEM and related skillsets, will eventually have an impact on the behavior of the demand side.

[37] We leave out an extensive literature on CEO and/or entrepreneur human capital for brevity.

Phillips and Zhdanov (2013)), shareholder litigation (Lin et. al. (2017)), hostile takeovers and anti-takeover policy (Atanassov (2013), (Sapra et al. (2014)), CEO overconfidence (Hirshleifer et al. (2012)), corporate tax rates (Mukherjee et al. (2017)), CEO connections (Faleye et al. (2015)), stock liquidity (Fang et al. (2014)), and analyst coverage (He and Tian (2013)).

We contribute to this literature by analyzing the corporate policy preference – between in-house development and international acquisition – of innovative U.S. firms in the area of intangible investment in human capital. We measure the effectiveness of the policy choice and adjustment to a shock in immigration policy – a national-level policy that affects all firms from specific industries – and the capital market reaction to those choices and adjustments.

6. Conclusions

Research on firm-level policy choices related to human capital investment or acquisition is scant. We establish a direct link between human capital investment policy and innovation outcomes for U.S. firms dependent on skilled labor using a plausibly exogenous policy shock. The policy choice is whether to acquire skilled labor in the international market or to invest in and develop it internally at the firm or host-country level. Before the 2004 immigration policy shock, large R&D intensive U.S. firms dependent on skilled immigrant workers had a significantly higher level and quality of innovation outcomes than the non-dependent firms. By the end of 2009, the innovation outcomes for the immigrant-dependent and non-dependent firms were almost identical. Overall, the policy choice made by these firms to acquire skilled human capital in the international market has been effective. The effectiveness of the policy is demonstrated by innovation outcome channel rather than by employee retrenchment channel.

Immigrant-dependent firms in our sample responded to the policy shock by reducing R&D investment to match the lower level of skilled immigrant labor input, by reducing employment at the firm level the year before the shock, and by increasing investment in existing human capital, measured by SG&A expense, beginning two years after the shock. The outcome for patenting intensity (patents/R&D) and quality (citation/patent) as well as capital market reaction to the adjustments made by the firms around the shock suggests that the immigrant-dependent firms responded appropriately. Although newly hired skilled immigrant workers in these firms are still paid 13% more than the prevailing real wage after the shock, we observe a decline in real wages not only for the newly hired skilled immigrants in these firms but also for similarly qualified host-country workers during this period. This is a strong argument against any unconditional assertion that skilled immigrants displace or substitute for similarly qualified host-country workers or that they depress the prevailing wages of the host-country workers. Our results indicate that there is potential heterogeneity among for-profit employers in their human capital acquisition policies, and in the costs and benefits associated with such policies. Our results can also be thought of as an out of sample test of two related works that provide vastly contradictory results for the question on whether skilled immigrant and host-country workers are substitutes or complements; the answer depends on who is hiring and which tail of the distribution the sample has been drawn from.

Consistent with the argument that, given the availability of skilled immigrant workers in the labor market, firms that rely on these workers for their innovation outcomes will, in equilibrium, have demand for these workers for specific jobs in which they have a comparative advantage. Complementing previous analyses, our findings show that U.S. firms, especially large research intensive and high-technology firms, are among the most successful in selecting immigrants whose activities increase innovation (and U.S. total factor productivity). This is an area of research with long-term policy implications, not only for immigration but also for higher education, especially in science, technology, engineering, and math.

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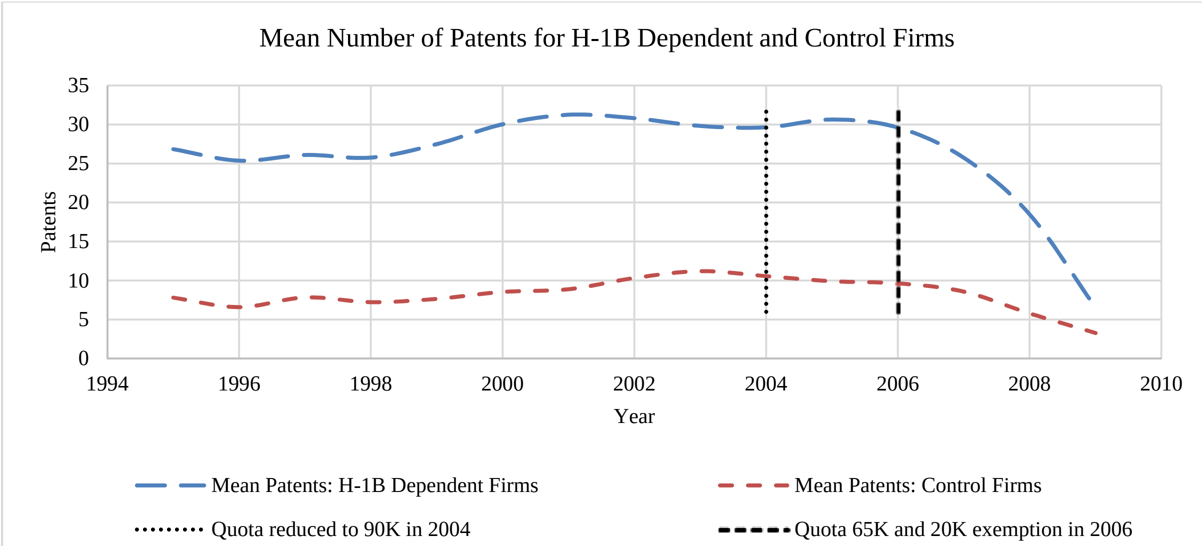

Figure 1: Average Number of Patents for the H-1B-Dependent (Treated) and Non-dependent (Control) Firms: 1995 – 2011

This figure displays the average number of patents for H-1B-dependent (treated) firms and non-dependent (control) firms for the period 1995 to 2011. Patents represents the total number of patents filed by a firm in a given year that are eventually granted and the data are obtained from UTPSO patent datasets.

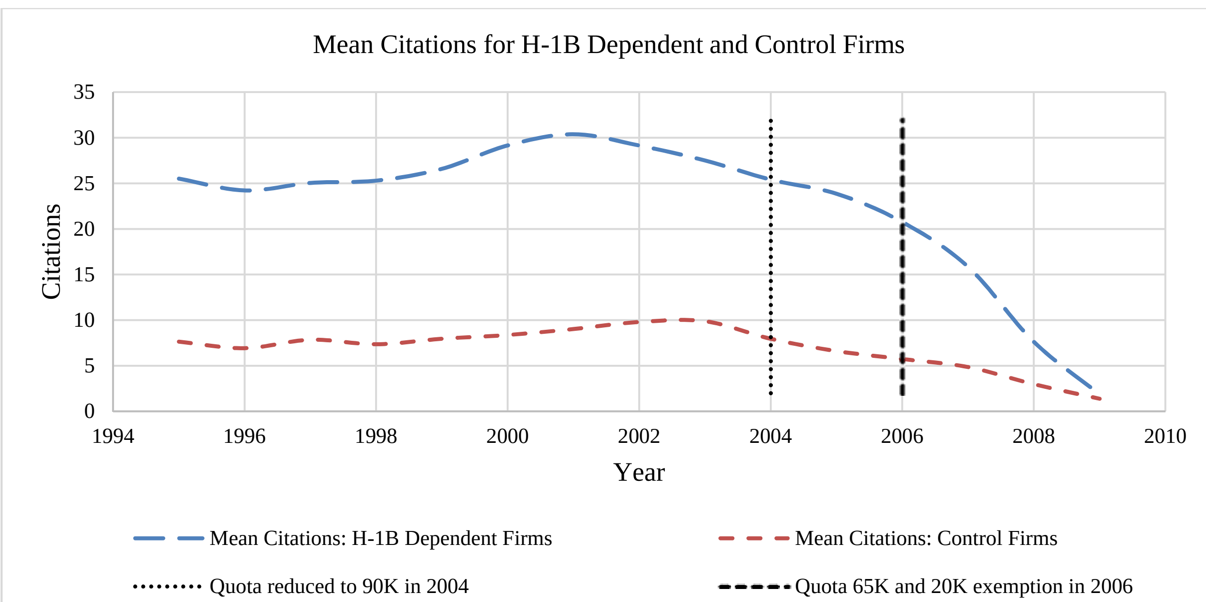

Figure 2: Average Citations for H-1B-Dependent (Treated) and the Non-dependent (Control) Firms: 1995 – 2011

This figure displays the average number of citations for the H-1B-dependent (treated) firms and the non-dependent (control) firms for the period 1995 till 2011. Citations represents the total number of citations for patents applied by a firm in a given year and the data are obtained from the UTPSO patent datasets.

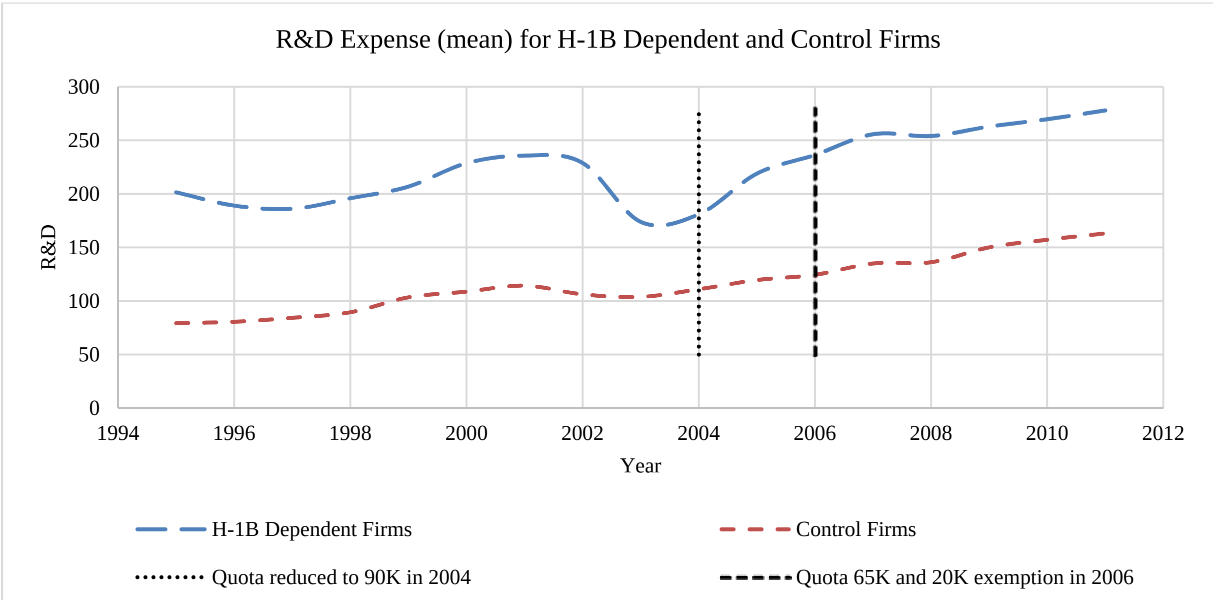

Figure 3A: Expenditure in Research and Development (R&D) for the H-1B-Dependent (Treated) and Non-dependent (Control) Firms

This figure presents the research and development (R&D) expenditures ($ million – 2001 real U.S. dollars) for H-1B dependent (treated) firms and non-dependent (control) firms for the period 1995 to 2011.

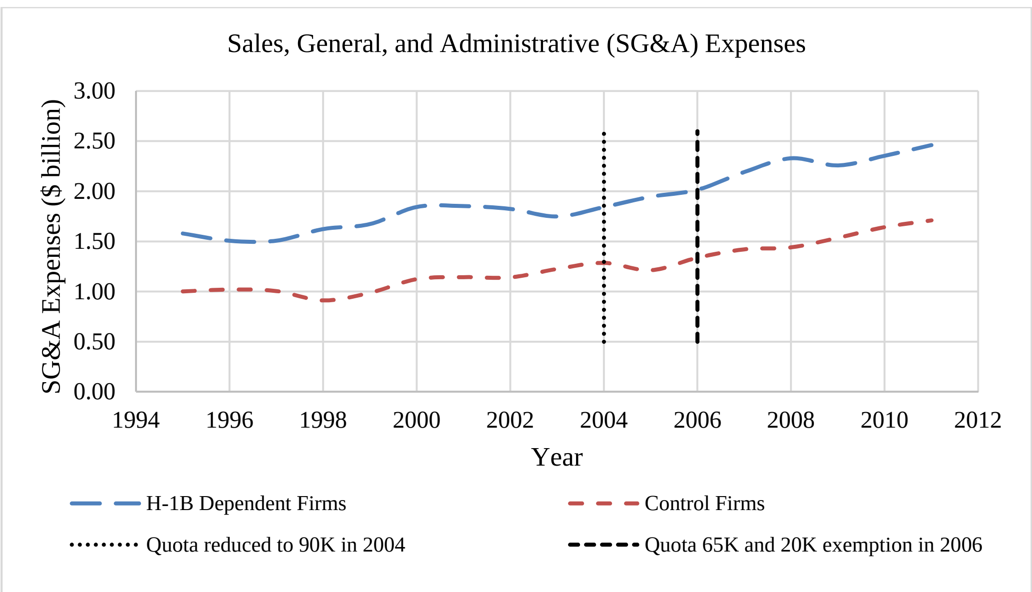

Figure 3B: Sales, General, and Administrative (SG&A) Expenses for the H-1B Dependent (Treated) and Non-dependent (Control) Firms for the years 1995-2011.

This figure presents the This figure presents the Sales, General, and Administrative (SG&A) expenses ($ billion – 2001 real U.S. dollars) for H-1B dependent (treated) firms and non-dependent (control) firms for the period 1995 to 2011.

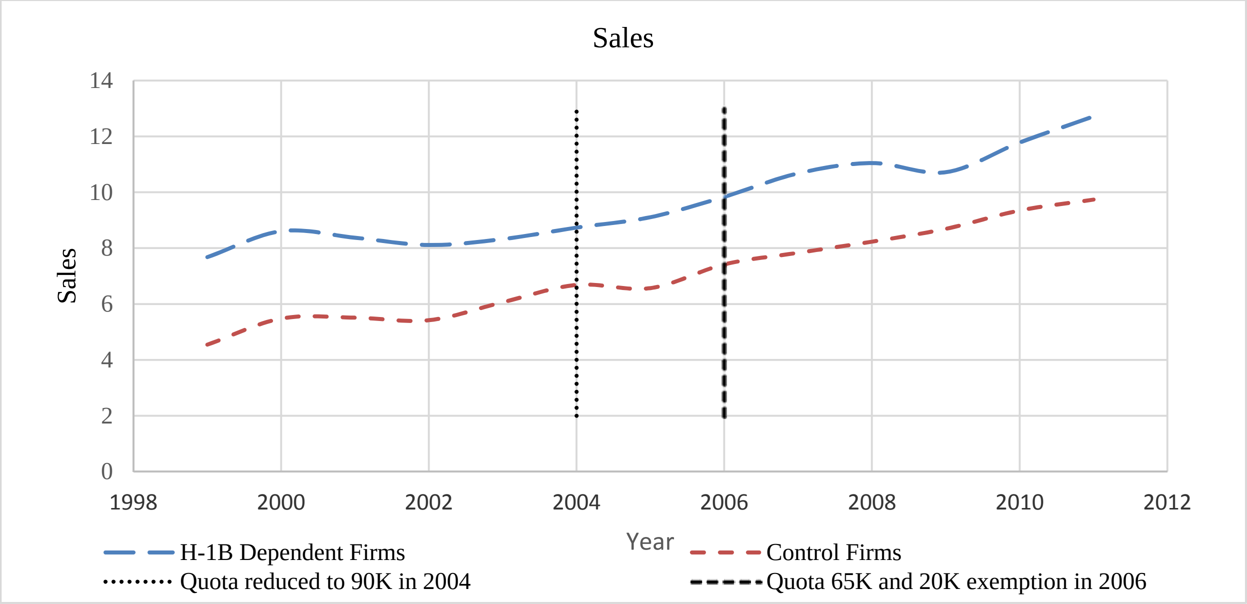

Figure 4: Sales ($ million - 2001 real U.S. dollars) for the H-1B Dependent (Treated) and Non-dependent (Control) Firms for the years 1995-2011

This figure presents the annual sales (revenue) ($ billion – 2001 real U.S. dollars) for H-1B dependent (treated) firms and non-dependent (control) firms for the period 1995 to 2011.

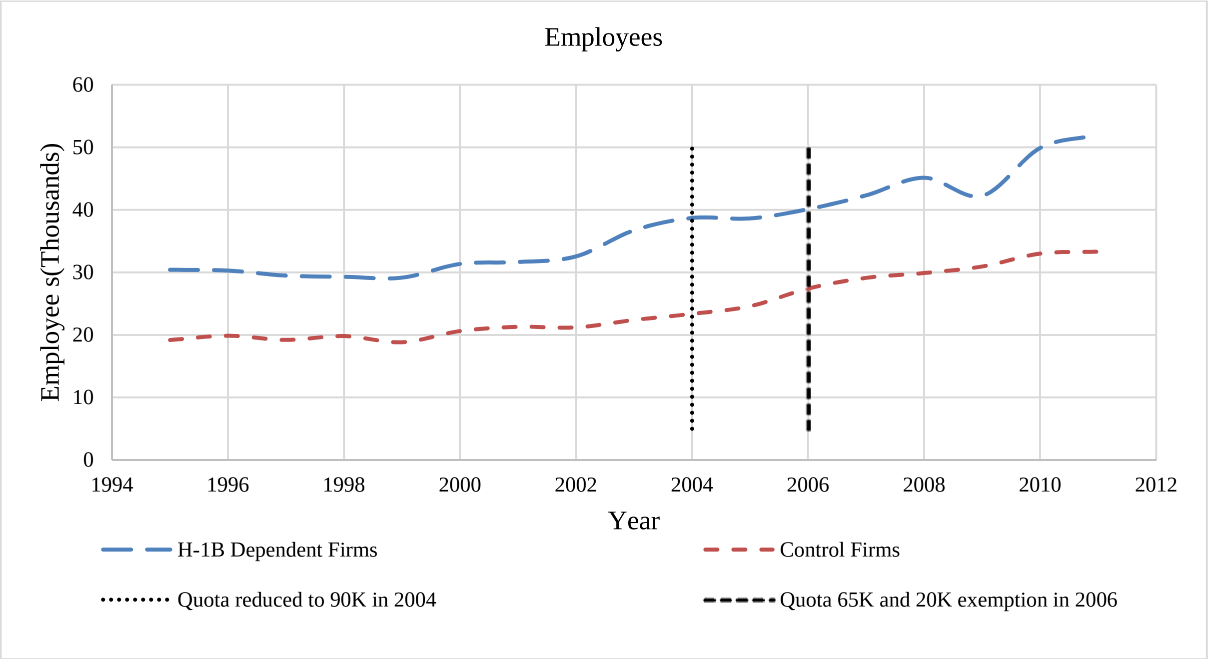

Figure 5: Employees (thousands) for the H-1B Dependent (Treated) and Non-dependent (Control) Firms for the years 1995-2011

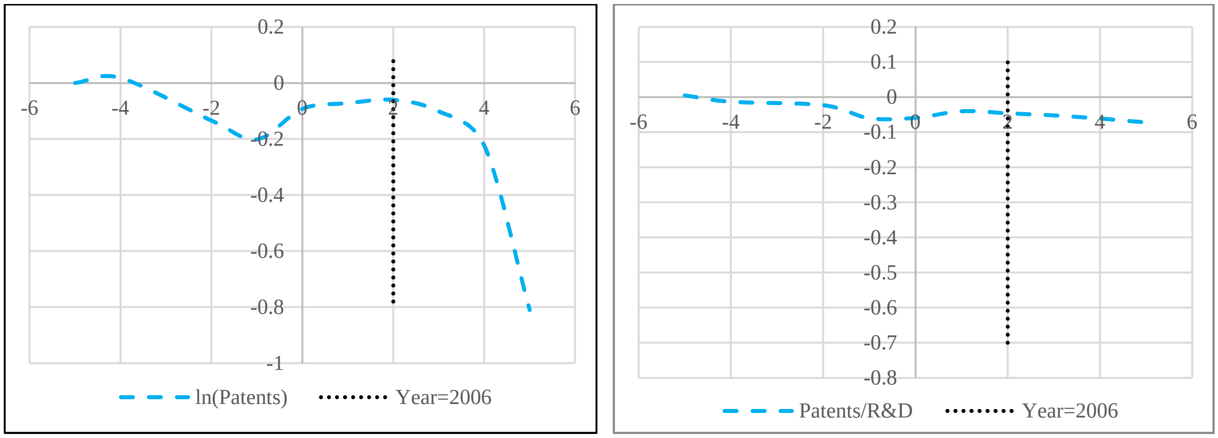

Figure 6: Event Study – Impact of Immigration Policy Induced Supply Shortage of H-1B Workers on the Level of Innovation

These event study figures graphically present the coefficients reported in models 3 and 4 in Table 7. Plots are for the estimated coefficients β_n (y-axis) against n from the estimation of equation (2). Innovation outcomes are normalized so that they equal zero in year 2004 (n=0).

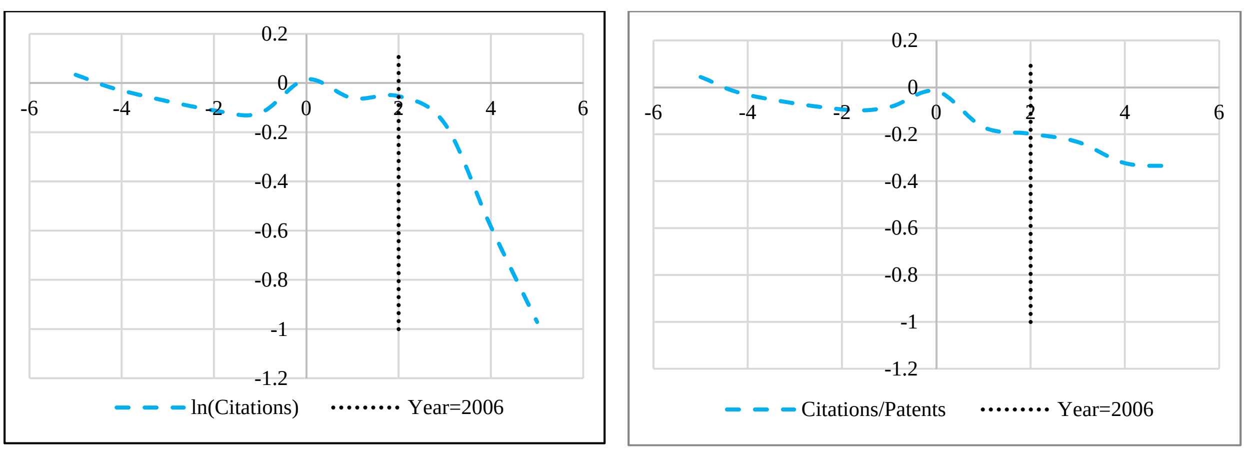

Figure 7: Event Study – Impact of Immigration Policy Induced Supply Shortage of H-1B Workers on the Quality of Innovation

These event study figures graphically present the coefficients reported in models 5 and 6 in Table 7. Plots are for the estimated coefficients β_n (y-axis) against n from the estimation of equation (2). Innovation outcomes are normalized so that they equal zero in year 2004 (n=0).

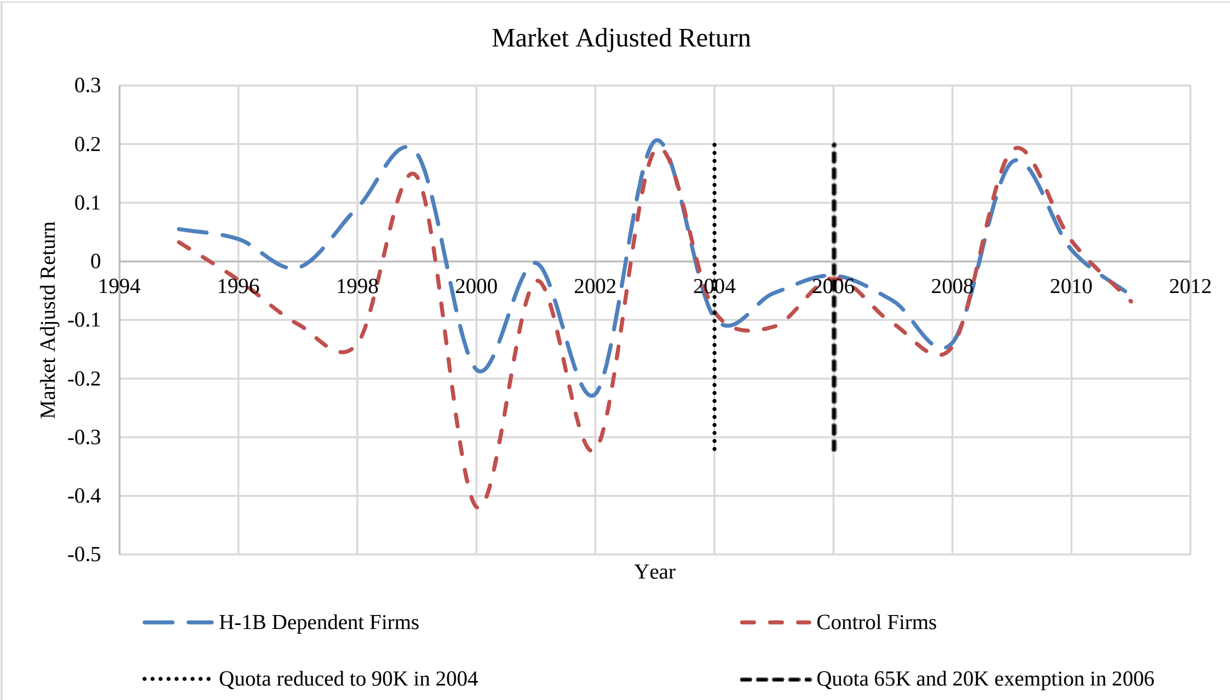

Figure 8: Market Adjusted Return for the H-1B Dependent (Treated) and Non-dependent (Control) Firms for the years 1995-2011.

Table 1: Characteristics of the Treated and Control Firms: Before and After Propensity-Score Matching

This table presents the characteristics of treated and control firms pre- and post-match. A firm is identified to be H-1B-dependent (treated) if a firm hires at least 20 H-1B employees in the years 2002 or 2003 (prior to policy shock in 2004). H-1B-dependent firms are matched with a control group in the year 2001 based on: firm size; leverage; market-to-book ratio; selling, general, and administrative expense (SG&A); research and development (R&D) expense; and patent over R&D within the same 4-digit SIC industries. Matching is performed based on the K-nearest neighbors (K=3) propensity-score matching method with replacement. This table presents diagnostic tests of the propensity score matching. The variable definitions are provided in Appendix A.1.

Panel A: Firm Characteristics Before and After Matching

		Treated	Control	%bias	%reduction in bias	t-stat	p-value
Ln(Assets)	Unmatched	8.384	4.728	148.2		20.08	0.00
	Matched	8.063	8.074	-0.5	99.7	-0.06	0.95
Leverage	Unmatched	0.200	0.371	-30.8		-3.44	0.00
	Matched	0.169	0.166	-0.6	98.1	0.17	0.87
Market-to-Book	Unmatched	2.041	3.573	-14.9		-1.59	0.11
	Matched	2.237	1.668	5.6	62.8	1.22	0.22
Ln(SG&A)	Unmatched	6.669	2.977	198.7		25.04	0.00
	Matched	6.636	6.628	0.4	99.8	0.05	0.96
Ln(R&D)	Unmatched	3.350	0.671	125.8		31.31	0.00
	Matched	4.085	3.699	18.1	85.6	1.49	0.14
Patent/R&D	Unmatched	1.773	0.173	26.0		10.74	0.00
	Matched	0.949	1.916	-15.7	39.5	-1.53	0.13
Ln(Employee)	Unmatched	2.556	-0.879	161.3		20.79	0.00
	Matched	2.401	2.267	6.3	96.1	0.70	0.48
Ln(Sales)	Unmatched	8.046	4.339	157.0		20.92	0.00
	Matched	7.848	7.709	5.9	96.3	0.71	0.48
Market Value of Equity	Unmatched	15.22	11.22	114.7		40.11	0.00
	Matched	13.12	12.94	1.4	98.8	0.11	0.91

Panel B: Summary Statistics at the Time of Matching (Year=2001)						
	Mean		Median		Standard Deviation	
	Treated (N=183)	Control (N=206)	Treated	Control	Treated	Control
Assets($ billion)	11.6	10.0	3.2	1.1	20.12	25.08
Leverage	0.169	0.180	0.124	0.125	0.194	0.205
Market-to-Book	2.237	1.757	1.451	0.782	2.703	7.995
SG&A ($ billion)	1.9	1.2	0.785	0.259	2.4	2.1
Employee (Thousands)	32.3	21.8	13.2	3.6	39.67	37.80
Revenue ($ billion)	8.4	5.5	2.4	0.89	11.0	10.7
ROA	0.109	0.028	0.104	0.075	0.125	0.238
Tobin's-q	3.068	2.533	2.371	1.579	2.734	7.393
Market Value of Equity ($ billion)	13.26	7.57	5.6	1.2	15.8	14.0
Return	-0.175	-0.211	-0.088	-0.084	0.637	0.744
Market Adjusted Return	-0.003	-0.033	0.053	0.057	0.598	0.690
R&D ($ million)	235.8	114.3	154.28	38.28	234.00	171.93
Patent	31.32	8.91	21.24	0.622	30.08	18.66
Patent/R&D	0.196	0.103	0.113	0.018	0.332	0.212
Citation	28.35	8.65	29.06	0.064	24.52	15.93
Citation/Patent	0.920	0.556	0.992	0.146	0.663	0.659

Panel C: Summary Statistics (Pooled): 1999-2009						
	Mean		Median		Standard Deviation	
	Treated (N=1863)	Control (N=1758)	Treated	Control	Treated	Control
Assets($ billion)	12.9	10.7	4.1	1.1	21.9	25.0
Leverage	0.167	0.183	0.137	0.139	0.173	0.196
Market-to-Book	2.378	1.627	1.237	0.820	5.669	4.801
SG&A ($ billion)	2.0	1.3	0.871	0.260	2.4	2.2
Employee (Thousands)	37.1	24.3	16.0	4.7	50.7	39.4
Revenue ($ billion)	9.1	6.3	3.3	1.0	11.7	11.3
ROA	0.120	0.066	0.116	0.094	0.133	0.180
Tobin's-q	3.206	2.441	2.049	1.612	5.619	4.685
Market Value of Equity ($ billion)	14.1	8.6	6.7	1.4	16.4	14.7
Return	-0.023	-0.084	0.039	0.017	0.619	0.723
Market Adjusted Return	-0.026	-0.078	0.003	-0.022	0.517	0.619
R&D ($ million)	224.15	116.50	132.91	23.86	234.17	189.63
Patent	26.93	8.84	11.79	0.0	29.06	19.21
Patent/R&D	0.138	0.095	0.113	0.005	0.214	0.199
Citation	20.99	6.94	7.53	0.0	23.46	15.12
Citation/Patent	0.625	0.380	0.50	0.00	0.610	0.577

Table 2: Distribution of the H-1B-Dependent Firms by Industries and the Average Number of H-1B Applications across Job Categories

Panel A reports the average number of H-1B applications, and the distribution of H-1B applications across various job categories, for each year, for the H-1B dependent firms. Panel B reports the distribution of H-1B-dependent (treated) firms and the matched control firms across different SIC industry classifications.

Panel A: Distribution of Number of H-1B Applications across Job Categories in 2002-2009							
Year	Number of Firms with H-1B Applications	Average Number of H-1B Applications	Computer-Related	Engineering and Architecture	Life Science, Social Sciences, Mathematics	Administrative Specializations	Education, Law, Arts and Entertainment
2002	87	71.88	65.14	3.03	24.14	5.80	1.87
2003	177	92.73	62.70	3.81	25.73	6.29	1.47
2004	136	126.59	64.15	3.61	23.96	6.57	1.71
2005	123	133.13	63.52	3.94	24.27	6.16	2.10
2006	127	150.50	48.66	27.15	15.64	6.72	1.82
2007	117	161.40	47.89	21.53	22.50	6.85	1.23
2008	109	163.50	60.88	6.22	25.61	6.31	0.98
2009	41	64.51	54.94	25.29	19.50	0.00	0.27

Panel B: Distribution of the Treated and the Control Firms by Industry								
SIC Industry	% Treated Firms	% Control Firms	Average Number of H-1B Applications	Computer-Related	Engineering and Architecture	Life Science, Social Sciences, Mathematics	Administrative Specializations	Education, Law, Arts and Entertainment
1000 – 1999	1.68	0.50	115.10	25.89	34.82	31.46	7.51	0.32
2000 – 2999	13.41	14.92	67.23	15.00	15.14	56.82	12.57	0.46
3000 – 3999	37.43	30.84	149.01	55.48	16.63	20.58	6.22	1.08
4000 – 4999	3.91	4.97	118.46	75.93	4.13	9.07	10.25	0.61
5000 – 5999	5.59	5.97	12.02	30.24	1.33	44.48	10.14	13.80
7000 – 7999	34.08	38.31	122.23	84.63	2.62	8.96	2.76	1.01
8000 – 8999	3.91	4.48	98	43.27	4.82	46.55	5.33	0.02

Table 3: Innovation Outcome and Investment in Innovation: Before and After Policy Shock

			Panel A		
Patents					
		H-1B Dependent Firms	Control Firms	1st Diff	2nd Diff (Diff-in-Diff)
	Pre-shock (1999-2003)	29.97	9.26	20.70*** (18.16)	
	Post-shock (2004-2009)	24.03	8.31	15.72*** (13.23)	-4.97*** (3.02)
	Post-shock -lag (2007-2009)	17.22	6.01	11.20*** (6.53)	-9.50*** (4.66)
Citations					
		H-1B Dependent Firms	Control Firms	1st Diff	2nd Diff (Diff-in-Diff)
	Pre-shock (1999-2003)	26.61	8.55	18.06*** (20.14)	
	Post-shock (2004-2009)	15.64	4.97	10.67*** (11.41)	-7.39*** (5.71)
	Post-shock-lag (2007-2009)	8.38	2.98	5.40*** (3.99)	-12.66*** (7.87)
			Panel B		
R&D ($Million)					
		H-1B Dependent Firms	Control Firms	1st Diff	2nd Diff (Diff-in-Diff)
	Pre-shock (1999-2003)	214.98	107.50	107.48 *** (10.89)	
	Post-shock (2004-2009)	232.89	127.58	105.31 *** (10.23)	-2.17 (0.88)
	Pre-shock (1999-2002)	225.18	108.28	116.90*** (11.07)	
	Post-shock (2003-2005)	190.68	111.08	79.60*** (6.13)	-37.30** (2.23)
SG&A ($Billion)					
		H-1B Dependent Firms	Control Firms	1st Diff	2nd Diff (Diff-in-Diff)
	Pre-shock (1999-2003)	1.79	1.12	0.67 *** (6.80)	
	Post-shock (2004-2009)	2.09	1.36	0.73 *** (7.14)	0.06 (0.43)
	Post-shock -lag (2007-2009)	2.26	1.46	0.79 *** (5.22)	0.13 (0.48)

Table 4: H-1B-Dependent Firms: Innovation Investments and Outcomes after Immigration Policy Shock

This table presents the impact of the immigration policy shock of 2004 on the H-1B-dependent firms, relative to the control group, on raw and normalized investment in innovation as measured by R&D and innovation outcome such as (natural log) patents, citations, and citations per patent before and after the immigration policy shock in year 2004. Panel A provides results on investment in innovation (R&D) and innovation outcome variable patents and panel B provides results on quality of innovation variable citations. The analyses are performed for the years 1999 – 2009. The H-1B-dependent firms are matched with a control group in the year 2001 (pre-sample year) based on: firm size; leverage; market-to-book ratio; selling, general, and administrative expense (SG&A); research and development (R&D) expense; and patents over R&D within the same 4-digit SIC industries. Matching is performed based on the K-nearest neighbors (K=3) propensity-score matching method with replacement. *H-1B Dependent* is an indicator variable that takes the value of 1 if the firm is an H-1B-dependent firm in the sample years and 0 otherwise. *After Policy Shock* is an indicator variable that equals 1 if the year is 2004 or later, and 0 otherwise. All variables are winsorized at the 1st and 99th percentile levels and expressed in 2001 dollars. Values of *t*-statistics are reported in parentheses and are based on robust standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Innovation Investment (R&D) and Outcome (Patents)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	$\ln(R\&D)_t$	$\left(\frac{R\&D}{Assset}\right)_t$	$\ln(Patent)_t$	$\ln(Patent)_{t+1}$	$\ln(Patent)_{t+2}$	$\ln(Patent)_{t+3}$	$\left(\frac{Patent}{R\&D}\right)_t$	$\left(\frac{Patent}{R\&D}\right)_{t+1}$	$\left(\frac{Patent}{R\&D}\right)_{t+2}$	$\left(\frac{Patent}{R\&D}\right)_{t+3}$
H1B Dependent *After Policy Shock	0.025	0.005	-0.134*	-0.291***	-0.498***	-0.720***	-0.036**	-0.023	-0.022*	-0.017
	(0.23)	(1.12)	(-1.87)	(-3.42)	(-4.68)	(-5.41)	(-2.17)	(-1.51)	(-1.67)	(-1.42)
ln(Assets)	0.345***	-0.038***	0.194***	0.148***	0.122**	0.093*	-0.020**	-0.028***	-0.018**	-0.008
	(5.86)	(-5.28)	(4.32)	(3.16)	(2.55)	(1.66)	(-2.06)	(-3.18)	(-2.31)	(-1.28)
Constant	0.843*	0.353***	0.169	0.692**	1.053***	1.299***	0.278***	0.336***	0.250***	0.164***
	(1.93)	(6.50)	(0.51)	(1.99)	(2.96)	(3.09)	(3.56)	(4.78)	(3.97)	(3.29)
Observations	3,615	3,615	3,615	3,444	3,271	3,118	3,562	3,444	3,269	3,113
R-squared	0.06	0.14	0.26	0.42	0.50	0.53	0.09	0.11	0.12	0.16
Number of firms	380	380	380	380	380	364	380	380	380	364
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Quality of Innovation: Citations								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	$\ln(Citation)_t$	$\ln(Citation)_{t+1}$	$\ln(Citation)_{t+2}$	$\ln(Citation)_{t+3}$	$\left(\frac{Citation}{Patent}\right)_t$	$\left(\frac{Citation}{Patent}\right)_{t+1}$	$\left(\frac{Citation}{Patent}\right)_{t+2}$	$\left(\frac{Citation}{Patent}\right)_{t+3}$
H1B Dependent*								
After Quota Shock	-0.210***	-0.466***	-0.652***	-0.822***	-0.162***	-0.047	-0.108**	-0.121**
	(-2.65)	(-4.58)	(-5.43)	(-6.05)	(-3.75)	(-0.85)	(-2.05)	(-2.47)
ln(Assets)	0.137***	0.127***	0.098*	0.077	0.050**	-0.029	-0.026	-0.020
	(3.61)	(2.64)	(1.90)	(1.31)	(2.52)	(-0.72)	(-0.84)	(-0.61)
Constant	0.489*	0.832**	1.201***	1.319***	0.305**	0.963***	0.979***	0.795***
	(1.73)	(2.33)	(3.13)	(2.99)	(2.03)	(3.18)	(3.92)	(3.13)
Observations	3,615	3,444	3,271	3,118	3,615	3,444	3,271	3,118
R-squared	0.33	0.43	0.49	0.51	0.28	0.13	0.17	0.20
Number of firms	380	380	380	364	380	380	380	364
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Top H-1B-Dependent Firms: Innovation Investments and Outcomes after Immigration Policy Shock

This table presents the impact of the immigration policy shock of 2004 on the top tercile of H-1B-dependent firms, relative to the control group, on raw and normalized investment in innovation as measured by R&D and innovation outcome such as (natural log) patents, citations, and citations per patent before and after the immigration policy shock in year 2004. H-1B dependent firms are ranked within industry into terciles. *Top H-1B Dependent* is an indicator variable that takes the value of 1 if the firm is in the top ranked H-1B-dependent firms and 0 otherwise. *After Policy Shock* is an indicator variable that equals 1 if the year is 2004 or later, and 0 otherwise. The analyses are performed for the years 1999 – 2009. All variables are winsorized at the 1st and 99th percentile levels and expressed in 2001 dollars. Values of *t*-statistics are reported in parentheses and are based on robust standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	$\ln(R\&D)_t$	$\left(\frac{R\&D}{Assset}\right)_t$	$\ln(Patent)_t$	$\left(\frac{Patent}{R\&D}\right)_t$	$\ln(Citation)_t$	$\left(\frac{Citation}{Patent}\right)_t$
Top H-1B dependent*After quota shock	0.005	0.003	-0.303***	-0.064**	-0.276**	-0.228***
	(0.04)	(0.59)	(-2.64)	(-2.39)	(-2.14)	(-3.19)
Ln(asset)	0.462***	-0.027***	0.140***	-0.016	0.106*	0.049*
	(6.39)	(-4.65)	(2.62)	(-1.26)	(1.91)	(1.69)
Constant	-0.323	0.258***	0.308	0.252**	0.479	0.246
	(-0.65)	(6.52)	(0.82)	(2.57)	(1.22)	(1.19)
Observations	1,961	1,961	1,961	1,934	1,961	1,961
R-squared	0.08	0.09	0.36	0.12	0.35	0.30
Number of firms	188	188	188	188	188	188
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Firms Dependent on H-1B Workers in Computer Related Occupations: Innovation Investments and Outcomes after Immigration Policy Shock

This table presents the impact of the immigration policy shock of 2004 on the firms most dependent on H-1B workers in computer related occupations, relative to the control group, on raw and normalized investment in innovation as measured by R&D and innovation outcome such as (natural log) patents, citations, and citations per patent before and after the immigration policy shock in year 2004. H-1B dependent firms are ranked into terciles within each industry based on LCA filing job description related to computer. *Computer Related H-1B Dependent* is an indicator variable that takes the value of 1 if the firm is in the top ranked H-1B-dependent firms from the above defined terclies and 0 otherwise. *After Policy Shock* is an indicator variable that equals 1 if the year is 2004 or later, and 0 otherwise. The analyses are performed for the years 1999 – 2009. All variables are winsorized at the 1st and 99th percentile levels and expressed in 2001 dollars. Values of *t*-statistics are reported in parentheses and are based on robust standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\ln(R\&D)_t$	(2) $\left(\frac{R\&D}{Assset}\right)_t$	(3) $\ln(Patent)_t$	(4) $\left(\frac{Patent}{R\&D}\right)_t$	(5) $\ln(Citation)_t$	(6) $\left(\frac{Citation}{Patent}\right)_t$
Computer Related H-1B dependent*After quota shock	-0.146	0.001	-0.239**	-0.034	-0.253**	-0.259***
	(-1.13)	(0.24)	(-2.07)	(-1.39)	(-2.12)	(-3.70)
Ln(asset)	0.470***	-0.028***	0.193***	-0.013	0.133**	0.050*
	(6.97)	(-5.91)	(2.75)	(-1.10)	(2.28)	(1.73)
Constant	-0.059	0.273***	0.024	0.227**	0.395	0.322
	(-0.12)	(8.04)	(0.05)	(2.39)	(0.94)	(1.53)
Observations	2,027	2,027	2,027	1,994	2,027	2,027
R-squared	0.07	0.10	0.39	0.09	0.39	0.34
Number of firms	192	192	192	192	192	192
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Dynamic Innovation Outcomes after the Immigration Policy Shock: H-1B-Dependent Firms Relative to Control Firms

This table presents the level of investment in innovation (R&D) and innovation outcomes (patents and citations) in the H-1B-dependent firms compared to a control group of firms before and after the immigration policy shock. The analyses are performed on the sub-sample for the years 1999 – 2009. The H-1B- dependent firms are matched with a control group in the year 2001(pre-sample year) based on firm size, leverage, market-to-book ratio, SG&A, R&D expenses, and patents over R&D within the same 4-digit SIC industries. Matching is performed based on the K-nearest neighbors (K=3) propensity-score matching method with replacement. *H-1B Dependent* is an indicator variable that equals 1 if the firm is H-1B dependent in the sample years, and 0 otherwise. Definitions of all variables are provided in Appendix A.1. All variables are winsorized at the 1st and 99th percentile levels and expressed in 2001 dollars. Values of *t*-statistics are reported in parentheses and are based on robust standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) ln(R&D)	(2) R&D/Asset	(3) ln(Patent)	(4) Patent/R&D	(5) ln(Citation)	(6) Citation/Patent
Post $_{-5,(t=1999)}$ × H-1B Dependent	0.031	0.005	-0.000	0.005	0.034	0.044
	(0.31)	(0.51)	(-0.00)	(0.18)	(0.33)	(0.69)
Post $_{-4,(t=2000)}$ × H-1B Dependent	0.021	0.007	0.018	-0.013	-0.030	-0.032
	(0.27)	(1.09)	(0.29)	(-0.75)	(-0.40)	(-0.56)
Post $_{-2,(t=2002)}$ × H-1B Dependent	0.101	0.001	-0.134**	-0.023	-0.111*	-0.094*
	(1.06)	(0.13)	(-2.29)	(-1.26)	(-1.76)	(-1.82)
Post $_{-1,(t=2003)}$ × H-1B Dependent	-0.543***	-0.003	-0.201***	-0.060***	-0.121*	-0.084
	(-2.64)	(-0.38)	(-3.05)	(-2.69)	(-1.70)	(-1.55)
Post $_{0,(t=2004)}$ × H-1B Dependent	-0.545***	-0.009	-0.092	-0.059**	0.015	-0.016
	(-2.61)	(-0.95)	(-1.24)	(-2.47)	(0.18)	(-0.27)
Post $_{1,(t=2005)}$ × H-1B Dependent	-0.319*	0.001	-0.072	-0.040	-0.061	-0.170***
	(-1.77)	(0.08)	(-0.92)	(-1.59)	(-0.64)	(-2.67)
Post $_{2,(t=2006)}$ × H-1B Dependent	-0.001	0.013	-0.060	-0.046*	-0.053	-0.198***
	(-0.01)	(1.59)	(-0.66)	(-1.83)	(-0.51)	(-3.07)
Post $_{3,(t=2007)}$ × H-1B Dependent	0.384**	0.017	-0.101	-0.052**	-0.165	-0.233***
	(2.06)	(1.64)	(-0.99)	(-2.04)	(-1.38)	(-3.35)
Post $_{4,(t=2008)}$ × H-1B Dependent	0.260	0.015*	-0.223*	-0.061**	-0.584***	-0.323***
	(1.25)	(1.68)	(-1.77)	(-2.26)	(-3.99)	(-4.47)
Post $_{5,(t=2009)}$ × H-1B Dependent	0.173	0.014	-0.810***	-0.072***	-0.971***	-0.336***
	(0.91)	(1.55)	(-5.01)	(-2.84)	(-5.75)	(-4.48)
ln(Asset)	0.355***	-0.038***	0.202***	-0.019*	0.143***	0.054***
	(5.99)	(-5.23)	(4.50)	(-1.96)	(3.79)	(2.71)
Constant	0.759*	0.349***	0.112	0.266***	0.434	0.259*
	(1.74)	(6.63)	(0.33)	(3.45)	(1.49)	(1.71)
Observations	3,615	3,615	3,615	3,562	3,615	3,615
R-squared	0.07	0.15	0.28	0.09	0.35	0.29
Number of firms	380	380	380	380	380	380
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Placebo Test: Using 1996-2002 sample and 1999 as pseudo shock-year

This table presents the level of investment in innovation (R&D) and innovation outcomes (patents and citations) in the H-1B-dependent firms compared to a control group of firms before and after the placebo shock year 1999. The analyses are performed on the sub-sample for the years 1995 – 2002. The H-1B- dependent firms are matched with a control group in the year 2001(pre-sample year) based on firm size, leverage, market-to-book ratio, SG&A, R&D expenses, and patents over R&D within the same 4-digit SIC industries. Matching is performed based on the K-nearest neighbors (K=3) propensity-score matching method with replacement. *H-1B Dependent* is an indicator variable that equals 1 if the firm is H-1B dependent in the sample years, and 0 otherwise. Definitions of all variables are provided in Appendix A.1. All variables are winsorized at the 1st and 99th percentile levels and expressed in 2001 dollars. Values of *t*-statistics are reported in parentheses and are based on robust standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln(R&D)	R&D/Asset	ln(Patent)	Patent/R&D	ln(Citation)	Citation/Patent
Post $_{-3,(t=1996)}$ × H-1B Dependent	0.024	0.016*	0.160*	0.078	0.139	0.021
	(0.33)	(1.78)	(1.78)	(1.55)	(1.45)	(0.32)
Post $_{-2,(t=1997)}$ × H-1B Dependent	0.012	0.023**	0.115	0.099*	0.160	0.077
	(0.12)	(2.27)	(1.19)	(1.67)	(1.58)	(1.10)
Post $_{-1,(t=1998)}$ × H-1B Dependent	-0.096	-0.009	0.172	0.038	0.191*	0.079
	(-0.81)	(-0.64)	(1.59)	(0.61)	(1.75)	(1.09)
Post $_{0,(t=1999)}$ × H-1B Dependent	-0.118	-0.012	0.295**	0.109*	0.276**	0.088
	(-0.87)	(-1.07)	(2.52)	(1.70)	(2.31)	(1.21)
Post $_{1,(t=2000)}$ × H-1B Dependent	-0.115	-0.008	0.326***	0.099	0.239**	0.024
	(-0.84)	(-0.84)	(2.72)	(1.51)	(1.99)	(0.33)
Post $_{2,(t=2001)}$ × H-1B Dependent	-0.146	-0.015	0.314**	0.108	0.263**	0.043
	(-1.06)	(-1.43)	(2.45)	(1.58)	(2.02)	(0.55)
Post $_{3,(t=2002)}$ × H-1B Dependent	-0.053	-0.013	0.181	0.079	0.126	-0.082
	(-0.34)	(-1.20)	(1.42)	(1.20)	(1.03)	(-1.04)
ln(Asset)	0.463***	-0.031***	0.159***	0.017**	0.184***	0.145***
	(14.70)	(-5.81)	(5.59)	(2.00)	(6.14)	(8.12)
Constant	-0.069	0.279***	0.296	0.074	0.092	-0.362***
	(-0.33)	(7.99)	(1.63)	(1.55)	(0.48)	(-3.11)
Observations	2,798	2,798	2,798	2,618	2,798	2,798
R-squared	0.31	0.14	0.13	0.02	0.13	0.10
Number of firms	380	380	380	380	380	380
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Alternative Hypotheses: Is "Hard Work" a "Skill" - Do Immigrant Employees Work Hard(er) and Long(er) or Substitute Host Country Workers?

This table presents the impact of the immigration policy shock of 2004 on the H-1B-dependent firms, relative to the control group, in terms of raw and normalized sales and employees. Models 1, 3, 5, 7 report analyses for the sample period 1999 – 2009 and Models 2, 4, 6, 8 report analyses for the sample period 1999 – 2011. Panel A reports variation in the dependent variables for the H-1B-dependent firms before and after the immigration policy shock compared to the matched control firms and Panel B reports time series variation of the dependent variables after the immigration policy shock. The H-1B-dependent firms are matched with a control group in 2001 based on firm size, leverage, market-to-book ratio, SG&A, R&D expenses, and patents over R&D within the same 4-digit SIC industries. Matching is performed based on the K-nearest neighbors (K=3) propensity-score matching method with replacement. *H-1B Dependent* is an indicator variable that takes the value of 1 if the firm is an H-1B-dependent firm in the sample years and 0 otherwise. *After Policy Shock* is an indicator variable that equals 1 if the year is 2004 or later, and 0 otherwise. The dependent variables measure the level of the corresponding variables in year *t*. Definitions of all the variables are provided in Appendix A1. All variables are winsorized at the 1st and 99th percentile levels and expressed in 2001 dollars. Values of *t*-statistics are reported in parentheses and are based on robust standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A										
	$\ln(Sales)_t$		$\left(\frac{Sales}{Asset}\right)_t$		ROA_t		$\ln(Employee)_t$		$\left(\frac{Employee}{Asset}\right)_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
H-1B Dependent* After Policy Shock	-0.037	-0.048	0.019	0.014	-0.154***	-0.158***	-0.019	-0.021	-0.000	-0.000
	(-0.90)	(-1.15)	(0.49)	(0.36)	(-3.30)	(-3.29)	(-0.47)	(-0.47)	(-0.40)	(-0.48)
Ln(Assets)	0.604***	0.636***	-0.322***	-0.314***	-0.008	-0.010	0.596***	0.628***	-0.002**	-0.002**
	(19.69)	(19.69)	(-8.04)	(-8.32)	(-0.13)	(-0.20)	(17.26)	(17.86)	(-2.24)	(-2.30)
Constant	2.604***	2.390***	3.392***	3.345***	-0.206	-0.182	-2.604***	-2.825***	0.023***	0.022***
	(11.68)	(10.22)	(11.14)	(11.58)	(-0.48)	(-0.47)	(-10.43)	(-11.03)	(3.26)	(3.43)
Observations	3,609	4,084	3,609	4,084	3,304	3,752	3,298	3,751	3,298	3,751
R-squared	0.48	0.49	0.25	0.25	0.04	0.04	0.44	0.45	0.03	0.03
Number of firms	380	380	380	380	380	380	380	380	380	380
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B										
	$\ln(Sales)_t$		$\left(\frac{Sales}{Asset}\right)_t$		ROA_t		$\ln(Employee)_t$		$\left(\frac{Employee}{Asset}\right)_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post $_{-5,(t=1999)}$ × H-1B Dependent	0.215***	0.214***	0.099*	0.099*	0.624***	0.623***	-0.016	-0.014	0.000	0.000
	(3.04)	(3.02)	(1.73)	(1.72)	(3.30)	(3.30)	(-0.39)	(-0.33)	(0.08)	(0.08)
Post $_{-4,(t=2000)}$ × H-1B Dependent	0.151***	0.154***	0.028	0.029	0.103	0.103	0.059*	0.063*	0.000	0.000
	(3.66)	(3.68)	(1.10)	(1.14)	(1.22)	(1.20)	(1.68)	(1.79)	(0.74)	(0.74)
Post $_{-2,(t=2002)}$ × H-1B Dependent	-0.013	-0.019	-0.014	-0.016	0.019	0.020	-0.029	-0.034	-0.000	-0.000
	(-0.37)	(-0.54)	(-0.41)	(-0.46)	(0.65)	(0.70)	(-0.94)	(-1.07)	(-1.07)	(-1.12)
Post $_{-1,(t=2003)}$ × H-1B Dependent	-0.013	-0.022	0.002	-0.001	-0.022	-0.020	-0.075**	-0.085**	-0.000	-0.000
	(-0.25)	(-0.43)	(0.04)	(-0.03)	(-0.62)	(-0.59)	(-2.18)	(-2.42)	(-0.98)	(-1.07)
Post $_{0,(t=2004)}$ × H-1B Dependent	-0.018	-0.027	0.018	0.015	-0.024	-0.023	-0.064	-0.072*	-0.000	-0.000
	(-0.32)	(-0.50)	(0.40)	(0.34)	(-0.62)	(-0.61)	(-1.58)	(-1.76)	(-0.51)	(-0.57)
Post $_{1,(t=2005)}$ × H-1B Dependent	0.006	-0.004	0.038	0.035	-0.003	-0.003	-0.031	-0.036	0.000	0.000
	(0.11)	(-0.08)	(0.79)	(0.74)	(-0.07)	(-0.07)	(-0.59)	(-0.68)	(0.05)	(0.06)
Post $_{2,(t=2006)}$ × H-1B Dependent	0.031	0.020	0.043	0.040	-0.016	-0.014	0.058	0.049	-0.000	-0.000
	(0.56)	(0.36)	(0.85)	(0.80)	(-0.37)	(-0.35)	(0.82)	(0.69)	(-0.08)	(-0.08)
Post $_{3,(t=2007)}$ × H-1B Dependent	0.097*	0.086	0.072	0.069	-0.011	-0.009	-0.043	-0.051	-0.000	-0.000
	(1.67)	(1.49)	(1.27)	(1.23)	(-0.23)	(-0.21)	(-0.57)	(-0.68)	(-0.32)	(-0.33)
Post $_{4,(t=2008)}$ × H-1B Dependent	0.087	0.076	0.066	0.063	0.000	0.002	-0.032	-0.038	-0.001	-0.001
	(1.63)	(1.43)	(1.11)	(1.07)	(0.01)	(0.05)	(-0.49)	(-0.57)	(-0.72)	(-0.72)
Post $_{5,(t=2009)}$ × H-1B Dependent	-0.011	-0.022	0.018	0.015	-0.025	-0.024	-0.083	-0.094	-0.002	-0.002
	(-0.20)	(-0.40)	(0.30)	(0.26)	(-0.56)	(-0.54)	(-1.12)	(-1.26)	(-0.89)	(-0.91)
Post $_{6,(t=2010)}$ × H-1B Dependent		0.004		0.017		-0.045		-0.001		-0.001
		(0.06)		(0.28)		(-0.91)		(-0.01)		(-0.91)

Post $_{7,(t=2011)}$ × H-1B Dependent		0.011		0.035		-0.013		-0.032		-0.000
		(0.14)		(0.56)		(-0.28)		(-0.35)		(-0.69)
ln(Assets)	0.608***	0.640***	- 0.321***	-0.313***	-0.003	-0.006	0.599***	0.631***	-0.002**	-0.002**
	(19.93)	(19.88)	(-7.88)	(-8.16)	(-0.05)	(-0.12)	(17.53)	(18.08)	(-2.27)	(-2.32)
Constant	2.465***	2.253***	3.336***	3.290***	-0.540	-0.513	- 2.624***	-2.844***	0.023***	0.022***
	(10.92)	(9.51)	(11.06)	(11.50)	(-1.23)	(-1.31)	(-10.67)	(-11.23)	(3.41)	(3.59)
Observations	3,609	4,084	3,609	4,084	3,304	3,752	3,298	3,751	3,298	3,751
R-squared	0.48	0.49	0.26	0.25	0.05	0.06	0.44	0.45	0.03	0.03
Number of firms	380	380	380	380	380	380	380	380	380	380
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Alternative Channels to Develop (vs. Source) Human Capital: Do Firms Increase Investment in Education and Training of Existing Employees When Skilled Immigrant Workers are in Short Supply?

This table presents the impact of the immigration policy shock of 2004 on the H-1B-dependent firms, relative to the control group, in terms of raw and normalized SG&A expense. Models 1, 3, 5, 7 report analyses for the sample period 1999 – 2009 and Models 2, 4, 6, 8 report analyses for the sample period 1999 – 2011. Panel A reports variation in the dependent variables for the H-1B-dependent firms before and after the immigration policy shock compared to the matched control firms and Panel B reports time series variation of the dependent variables after the immigration policy shock. The H-1B-dependent firms are matched with a control group in 2001 based on firm size, leverage, market-to-book ratio, SG&A, R&D expenses, and patents over R&D within the same 4-digit SIC industries. Matching is performed based on the K-nearest neighbors (K=3) propensity-score matching method with replacement. *H-1B Dependent* is an indicator variable that takes the value of 1 if the firm is an H-1B-dependent firm in the sample years and 0 otherwise. *After Policy Shock* is an indicator variable that equals 1 if the year is 2004 or later, and 0 otherwise. The dependent variables measure the level of the corresponding variables in year *t*. Definitions of all the variables are provided in Appendix A1. All variables are winsorized at the 1st and 99th percentile levels and expressed in 2001 dollars. Values of *t*-statistics are reported in parentheses and are based on robust standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A						
	Log(SG&A expense)		SG&A/Sales		SG&A/Employee	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
H1B dependent*After quota shock	0.084**	0.091**	0.110***	0.116***	1.361	3.644
	(2.02)	(2.00)	(2.82)	(3.10)	(0.22)	(0.58)
Ln(Asset)	0.597***	0.619***	0.024	0.016	-3.771	-4.948
	(19.13)	(19.35)	(0.62)	(0.47)	(-0.61)	(-0.87)
Constant	1.568***	1.412***	0.426	0.470*	121.569***	129.835***
	(6.74)	(5.91)	(1.44)	(1.79)	(2.60)	(2.99)
Observations	3,506	3,979	3,501	3,971	3,265	3,716
R-squared	0.53	0.53	0.02	0.02	0.01	0.01
Number of firms	380	380	380	380	380	380
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Panel B						
	Log(SG&A expense)		SG&A/Sales		SG&A/Employee	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Post $_{-5,(t=1999)}$ × H-1B Dependent	0.043	0.042	-0.312**	-0.310**	6.776	6.946
	(0.87)	(0.85)	(-2.14)	(-2.13)	(0.78)	(0.79)
Post $_{-4,(t=2000)}$ × H-1B Dependent	0.067**	0.071**	-0.185***	-0.185***	-1.902	-2.081
	(2.09)	(2.14)	(-2.81)	(-2.82)	(-0.25)	(-0.28)
Post $_{-2,(t=2002)}$ × H-1B Dependent	-0.010	-0.014	-0.085	-0.083	5.149	5.250
	(-0.37)	(-0.52)	(-1.21)	(-1.19)	(0.70)	(0.72)
Post $_{-1,(t=2003)}$ × H-1B Dependent	0.013	0.005	0.008	0.011	12.951	13.314*
	(0.32)	(0.12)	(0.25)	(0.33)	(1.62)	(1.66)
Post $_{0,(t=2004)}$ × H-1B Dependent	0.025	0.018	0.035	0.038	8.577	8.727
	(0.54)	(0.39)	(1.04)	(1.12)	(0.89)	(0.90)
Post $_{1,(t=2005)}$ × H-1B Dependent	0.032	0.026	-0.036	-0.033	3.410	3.530
	(0.74)	(0.61)	(-0.48)	(-0.44)	(0.32)	(0.33)
Post $_{2,(t=2006)}$ × H-1B Dependent	0.100**	0.092*	0.006	0.009	0.546	0.548
	(2.04)	(1.87)	(0.14)	(0.19)	(0.04)	(0.04)
Post $_{3,(t=2007)}$ × H-1B Dependent	0.174***	0.166**	-0.016	-0.014	-0.244	0.102
	(2.68)	(2.54)	(-0.38)	(-0.32)	(-0.02)	(0.01)
Post $_{4,(t=2008)}$ × H-1B Dependent	0.199***	0.190***	-0.015	-0.013	11.256	11.471
	(2.85)	(2.71)	(-0.35)	(-0.30)	(1.07)	(1.08)
Post $_{5,(t=2009)}$ × H-1B Dependent	0.170**	0.160**	0.001	0.003	12.909	12.746
	(2.31)	(2.19)	(0.02)	(0.06)	(1.20)	(1.19)
Post $_{6,(t=2010)}$ × H-1B Dependent		0.181**		0.007		14.314

		(2.27)		(0.16)		(1.35)
Post $_{7,(t=2011)}$ × H-1B Dependent		0.154*		0.030		19.335*
		(1.84)		(0.52)		(1.72)
Ln(Asset)	0.597***	0.619***	0.020	0.013	-4.140	-5.382
	(19.07)	(19.21)	(0.53)	(0.38)	(-0.67)	(-0.94)
Constant	1.543***	1.390***	0.609*	0.650**	120.943**	129.613***
	(6.51)	(5.70)	(1.88)	(2.21)	(2.45)	(2.80)
Observations	3,506	3,979	3,501	3,971	3,265	3,716
R-squared	0.54	0.54	0.03	0.03	0.01	0.01
Number of firms	380	380	380	380	380	380
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Falsification Tests: Effects on Other Outcome Measures -- Market Value of Equity, ROA, and Annual Return

This table presents the impact of the immigration policy shock of 2004 on the H-1B-dependent firms, relative to the control group, in terms of market value of equity, ROA, raw annual return, and market adjusted annual return. Models 1, 3, 5, 7 report analyses for the sample period 1999 – 2009 and Models 2, 4, 6, 8 report analyses for the sample period 1999 – 2011. Panel A reports variation in the dependent variables for the H-1B-dependent firms before and after the immigration policy shock compared to the matched control firms and Panel B reports time series variation of the dependent variables after the immigration policy shock. The H-1B dependent firms are matched with a control group in 2001 based on firm size, leverage, market-to-book ratio, SG&A, R&D expenses, and patents over R&D within the same 4-digit SIC industries. Matching is performed based on the K-nearest neighbors (K=3) propensity-score matching method with replacement. *H-1B Dependent* is an indicator variable that takes the value of 1 if the firm is an H-1B dependent firm in the sample years and 0 otherwise. *After Policy Shock* is an indicator variable that equals 1 if the year is 2004 or later, and 0 otherwise. The dependent variables measure the level of the corresponding variables in year *t*. Definitions of all the variables are provided in Appendix A1. All variables are winsorized at the 1st and 99th percentile levels and expressed in 2001 dollars. Values of *t*-statistics are reported in parentheses and are based on robust standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Impact of Immigration Policy Shock on Other Outcome Measures

VARIABLES	$\ln(MkEQ)_t$		$Tobin's-q_t$		$Return_t$		$MarketAdjusted\ Return_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
H-1B Dependent*After Policy Shock	-0.170**	-0.194***	-0.446	-0.475	0.034	0.026	0.033	0.025
	(-2.38)	(-2.64)	(-1.43)	(-1.50)	(1.09)	(0.85)	(1.06)	(0.83)
ln(Assets)	0.885***	0.869***	-1.599***	-1.497***	-0.219***	-0.208***	-0.203***	-0.193***
	(16.38)	(17.05)	(-3.88)	(-3.80)	(-7.66)	(-8.42)	(-7.30)	(-8.05)
Constant	1.733***	1.871***	18.828***	18.143***	1.991***	1.911***	1.647***	1.581***
	(4.26)	(4.87)	(5.67)	(5.70)	(9.30)	(10.30)	(7.95)	(8.78)
Observations	3,254	3,694	3,252	3,692	3,218	3,640	3,218	3,640
R-squared	0.38	0.38	0.12	0.13	0.36	0.36	0.11	0.11
Number of firms	380	380	380	380	368	368	368	368
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Dynamic Effect of the Shock on Other Outcome Measures								
VARIABLES	$\ln(MkEQ)_t$		$Tobin's-q_t$		$Return_t$		$MarketAdjusted\ Return_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Post_{-5,(t=1999)} \times$ H-1B Dependent	-0.021	-0.020	1.425	1.424	0.106	0.103	0.109	0.106
	(-0.17)	(-0.16)	(1.00)	(1.00)	(0.93)	(0.90)	(0.96)	(0.94)
$Post_{-4,(t=2000)} \times$ H-1B Dependent	0.038	0.037	1.497*	1.507*	0.191	0.186	0.184	0.180
	(0.47)	(0.45)	(1.86)	(1.88)	(1.63)	(1.59)	(1.61)	(1.58)
$Post_{-2,(t=2002)} \times$ H-1B Dependent	-0.004	-0.005	0.420	0.399	0.129	0.120	0.127	0.119
	(-0.05)	(-0.07)	(1.04)	(0.99)	(1.60)	(1.49)	(1.64)	(1.53)
$Post_{-1,(t=2003)} \times$ H-1B Dependent	-0.115	-0.111	0.163	0.169	0.124	0.114	0.118	0.108
	(-1.26)	(-1.22)	(0.36)	(0.38)	(1.42)	(1.31)	(1.42)	(1.30)
$Post_{0,(t=2004)} \times$ H-1B Dependent	-0.149*	-0.141	0.203	0.203	0.101	0.090	0.097	0.086
	(-1.66)	(-1.59)	(0.47)	(0.47)	(1.29)	(1.14)	(1.28)	(1.14)
$Post_{1,(t=2005)} \times$ H-1B Dependent	-0.156*	-0.154*	0.223	0.210	0.183**	0.171**	0.182**	0.171**
	(-1.74)	(-1.73)	(0.51)	(0.49)	(2.47)	(2.31)	(2.56)	(2.40)
$Post_{2,(t=2006)} \times$ H-1B Dependent	-0.158	-0.152	0.212	0.189	0.136	0.126	0.132*	0.122
	(-1.51)	(-1.47)	(0.49)	(0.44)	(1.62)	(1.50)	(1.65)	(1.53)
$Post_{3,(t=2007)} \times$ H-1B Dependent	-0.213**	-0.204**	0.171	0.151	0.169**	0.159*	0.169**	0.159*
	(-2.07)	(-1.99)	(0.39)	(0.35)	(2.00)	(1.88)	(2.05)	(1.93)
$Post_{4,(t=2008)} \times$ H-1B Dependent	-0.155	-0.152	0.357	0.298	0.157	0.144	0.150	0.140
	(-1.24)	(-1.21)	(0.75)	(0.64)	(1.61)	(1.50)	(1.64)	(1.52)
$Post_{5,(t=2009)} \times$ H-1B Dependent	-0.330**	-0.328**	0.194	0.160	0.124	0.114	0.113	0.104
	(-2.38)	(-2.36)	(0.40)	(0.34)	(1.42)	(1.31)	(1.34)	(1.23)
$Post_{6,(t=2010)} \times$ H-1B Dependent		-0.333***		0.138		0.102		0.102
		(-2.97)		(0.29)		(1.24)		(1.29)

Post $_{7,(t=2011)}$ × H-1B Dependent		-0.318**		0.222		0.131		0.129
		(-2.43)		(0.47)		(1.59)		(1.65)
ln(Assets)	0.890***	0.873***	-1.540***	-1.448***	-0.220***	-0.207***	-0.203***	-0.193***
	(16.35)	(17.04)	(-3.84)	(-3.78)	(-7.71)	(-8.45)	(-7.32)	(-8.06)
Constant	1.711***	1.844***	17.656***	17.031***	1.934***	1.852***	1.588***	1.520***
	(4.12)	(4.71)	(5.53)	(5.58)	(8.62)	(9.39)	(7.29)	(7.94)
Observations	3,254	3,694	3,252	3,692	3,218	3,640	3,218	3,640
R-squared	0.38	0.38	0.13	0.13	0.37	0.36	0.12	0.11
Number of firms	380	380	380	380	368	368	368	368
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 12: Alternative Hypothesis: Do Skilled Immigrant Workers Depress Host-Country Wages?

The table presents the mean of offered wages to H-1B employees and the prevailing wage before (high new immigrant inflow) and after (low new immigrant inflow) the immigration policy shock. Wage premium is the difference between wage and prevailing wage. Wages expressed in 2002 dollars. Number of Observations is the number of firms, not the number of LCAs.

	Before (year < 2004) (obs. = 263)	After (years 2004– 2009) (obs. = 1,152)	*p*-value for the Difference	After (years 2004– 2007) (obs. = 893)	*p*-value for the Difference
H-1B Wage	72,703	71,009	0.03	70,965	0.03
Prevailing Wage	63,761	62,729	0.15	62,665	0.14
Wage Premium	8,906	8,261	0.09	8,307	0.12

Appendix - Table A.1: Variable Definitions:

Variable	Source	Definition
Types of petitions		
Initial employment	USCIS	Petitions for initial employment are filed for the first time H-1B workers.
Continuing employment	USCIS	Petitions for continuing employment are the filings for foreign workers who are already in the U.S. and refer to extensions, sequential employment, and concurrent employments. Extensions refer to petitions for H-1B workers to provide extension to work beyond the initial three-year period for up to a total of six years. Petitions for sequential employment are filings for workers transferring between H-1B employers within the six-year period. Concurrent employment petitions refer to filings for H-1B workers intending to simultaneously work for a second employer.
Petitions filing and approvals		
% Petitions filed initial	USCIS	Number of petitions filed for initial employment divided by the total number of petitions filed in a given fiscal year
% Petitions filed continuing	USCIS	Number of petitions filed for continuing employment divided by the total number of petitions filed in a given fiscal year
% Petitions approved	USCIS	Total number of petitions approved divided by the total number of petitions filed in a given fiscal year
% Petitions approved initial	USCIS	Number of petitions approved for initial employment divided by the total number of petitions approved in a given fiscal year
% Petitions approved continuing	USCIS	Number of petitions approved for continuing employment divided by the total number of petitions approved in a given fiscal year
% Initial filed approved	USCIS	Number of petitions approved for initial employment divided by the total number of petitions filed for initial employment in a given fiscal year
% Continuing filed approved	USCIS	Number of petitions approved for continuing employment divided by the total number of petitions filed for continuing employment in a given fiscal year
Firm Characteristics		
Assets	Compustat	Total assets (US $ million) of a firm in a given year
Sales	Compustat	Total sales (US $ million) of a firm in a given year
Tobin's-q	Compustat	Sum of total assets plus market value of equity minus book value of equity divided by total assets [Compustat (AT + CSHO x PRCC_F - CEQ) / AT)].
Market-to-book asset	Compustat	(CSHO x PRCC_F + DLC + DLTT - CEQ)/AT;
ROA	Compustat	Earnings before interest and taxes, depreciation, and amortization divided by lag of total assets (Compustat EBITDA / lag AT)
Leverage	Compustat	Total debt, defined as debt in current liabilities plus long-term debt, divided by total assets [(DLC + DLTT) / AT].
Market Value of Equity	Compustat	Total market value of equity: CSHO x PRCC_F
Employee	Compustat	Total number of employees (Thousands) of a firm in a year
SG&A	Compustat	Selling, General, and Administrative expenditures ($ million) of a firm in a year
R&D	Compustat	R&D expenditures (US $ million) incurred by a firm in a given year (XRD)
Patents	https://iu.app.box.com/patents	Total number of patents filed by a firm in a year that are eventually granted. The number of patents is adjusted for truncation bias because, on average, there is a two years lag between the time a patent is filed and granted. Adjusted patents are computed by dividing the number of patents for each firm-year by the mean number of patents by all firms in the same technology class and year.
Citations	https://iu.app.box.com/patents	Total number of citations for patents for a firm in a given year. The measure is adjusted for truncation bias because more recent patents will have shorter time to accumulate

		citations compared to earlier patents in the sample. The adjusted measure is computed by dividing the total number of citations for each firm-year by the mean number of citations of the same patent technology class in a given year.
H-1B Dependent and Control Firms		
H-1B Dependent	Labor Condition Application (LCA) with the Department of Labor (DOL)	A firm is identified to be H-1B dependent (treated firm) if a firm hires at least 20 H-1B employees in any year within the sample period 2002-2011. For robustness, we also define firms that file H-1B petitions equivalent to 0.5% of the total workforce, as H-1B dependent firms.
Control Firms	Compustat	The H-1B dependent firms are matched with a control group in the year 2001 based on firm size, leverage, market-to-book, log SG&A, and log R&D expenditures within the same 4 digit SIC industries. Matching is performed based on K-nearest neighbors (K=3) propensity score matching method with replacement.
Top H-1B Dependent	LCA of Department of Labor (DOL)	In each year, the H-1B dependent firms are ranked and grouped into terciles, within their respective SIC industries, based on the percentage of H-1B employees hired by the firms. Percentage of H-1B employees hired by a firm is computed by dividing the number of H-1B petitions filed by the firm with the total number of employees in the firm. *Top H-1B Dependent* is an indicator variable that takes the value of 1 if a firm belongs to the top ranked group within the firm's industry in a given year, and 0 otherwise.
Top2 H-1B Dependent	LCA of Department of Labor (DOL)	*Top2 H-1B Dependent* is an indicator variable that takes the value of 1 if a firm belongs to the top two ranked tercile groups based on the percentage of H-1B employee petitions filed by the firm within the firm's industry in a given year, and 0 otherwise.
Bottom H-1B Dependent	LCA of Department of Labor (DOL)	*Bottom H-1B Dependent* is an indicator variable that takes the value of 1 if a firm belongs to the bottom ranked tercile group based on the percentage of H-1B employee petitions filed by the firm within the firm's industry in a given year, and 0 otherwise.

Internet Appendix

Human Capital, Skilled Immigrants, and Innovation

1. Additional Comparison between the Immigrant-Dependent and Non-Dependent Firms

Internet Appendix Figure IA.1 shows the investment in innovation relative to firm size measured by the total asset. On average, the treated (control) firms spend between 6% (5.5%) and 8% (8%) of their assets on R&D during our sample period. There is no economic or statistical difference between the groups. The large spike between 1995 and 1998 (1998-1999 for the control group) for the treatment group of firms for the R&D expense relative to size and subsequent decline is driven by the denominator or the firm size. Both group of firms experienced large growth (in asset) during this period.

We normalize the innovation outcome or the number of patents by the investment in R&D, but the difference between the groups does not go away (Internet Appendix Figure IA.2). For every $100 million spent in R&D, the H-1B-dependent firms had 13 patents, on average, in 2004, and the non-dependent firms had 8 patents. Beginning in 2007, the difference narrows, and in 2009 both groups of firms have 2 patents for every $100 million investment in R&D (all investments in 2001 dollars). While both groups see a decline in patenting rate relative to R&D investment, perhaps due to some unobserved structural reasons, the decline among the immigrant dependent groups are much sharper and the difference in the decline between the two groups are statistically significant.

Internet Appendix Figure IA.3 shows the time series trend in the market value of equity for both group of firms. Both groups display the same positive and negative shocks in equity value during the NASDAQ rise and crash of the late 1990s and early 2000s as well as the great recession of the 2009. When we compare the trend in size, measured by total assets, for the two groups of firms, again we observe parallel trends (Internet Appendix Figure IA.4).

These additional results graphically confirm that the changes in innovation investments and outcome presented in Figures 1 to 3 in the main text of the paper and supported by Figure IA.2 are unique and not random.

2. Reconciling Our Results with Doran, Gelber, and Isen (2016)

In a related work, Doran et al. (2016; henceforth DGI) use a random assignment design based on the H-1B visa lottery outcome and estimate the partial equilibrium impact of H-1B workers on the innovation and employment of citizen or host country workers at the firm level. They find that firms that win the H-1B lottery do not innovate more than the firms that do not win the lottery. In addition, they observe a substitution or crowding-out effect for host-country workers. In other words, H-1B workers from firms that win the visa lottery displace host-country workers. Here we try to reconcile these contradictory results.

DGI measure the partial equilibrium results of the impact of the marginal H-1B workers, whose applications were submitted on a specific, albeit ex ante unknown date, subject to the lottery, for the 2006–2007 sample years, on firms that won the H-1B lottery. Our results measure the impact of almost all the non-incumbent H-1B workers for the H-1B-dependent firms in the Compustat universe during the sample period 2002–2009, not only for the firms subject to the lottery in 2006–2007. Hence, our results are closer to the general equilibrium results than those in DGI.

There are other important differences between our sample and that of DGI. For instance, the largest fraction of our sample, 37% of all firms, comes from SIC code 3000–3999 (99% in NAICS 31, 32, 33) These are industries specializing in medical, surgical, dental, ophthalmic, and electromedical devices; search and navigation equipment; process control devices; aircraft-, space vehicle-, and propulsion unit manufacturing; ship-building, railroad equipment, military and civilian transport equipment; electronics, computer, and electrical equipment manufacturing; downstream petroleum products; manufacturing of internal combustion engines and gas turbines; construction and oilfield service equipment; mining and heavy construction machinery; industrial machinery; and motor, generator, transformer, household appliance, rubber, glass, industrial metal, metallurgy, and metal alloy processing industries. IBM, Intel, HP, Apple, Applied Materials, GE, General Dynamics, and others belong to this group.

Another 13% of our sample comes from SIC code 2000–2999. Industrial organic and inorganic chemicals, petroleum products, drugs and pharmaceutical products, fertilizers, petroleum refining, biological products, pigments, and explosives, among others, fall within this group. Dow Chemical, DuPont, Genentech, Pfizer, and Merck belong to this group. Within the 3000–3999 SIC firms, 55% of H-1B workers have a computer-related background and another 21% have a life sciences, social sciences, and mathematics background. Within SIC 2000–2999 firms, 57% of H-1B workers come with a life sciences, social sciences, or mathematics background, 20% with a computer-related background, and 15% with an engineering and architecture background. Hence these H-1B workers do not fall into the generic “systems analyst” and “programmer” category where most of the concern regarding outsourcing lies.

In contrast, 56% of the DGI sample comes from NAICS 54 (Professional, Scientific, and Technical Services). For firms with fewer than 30 (and 10) employees, where their results are strongest, 65% of the sample comes from NAICS 54, which primarily corresponds to SIC 73 and SIC 87 and includes miscellaneous computer services, payroll and HR consulting services, media, graphic design, and advertising services. In contrast, only 34% of our sample comes from SIC code 7000–7999 and 4% from SIC 8000–8999. Given these distributions, and given that 82% of the H-1B LCAs in SIC code 7000–7999 have computer-related specialization, more of these firms are likely to specialize in providing information technology systems support in computer-related services.

The very characteristic that DGI use (pg. 20 and Panel A of Table 2) to argue that the firms that file petitions on the lottery day are more innovative because these firms have a 17% higher probability of coming from professional, scientific, and technical services industries (NAICS 54) confirms that their sample H-1B workers/firms are more representative of service sector workers/firms (as opposed to manufacturing), and are more likely to represent the less innovative outsourcing firms/industries, even if the service is in the "professional, scientific, and technical service" industry.[38] Given that the fraction of firms in the DGI sample that come from the service industry classification is almost twice that in our sample, a larger proportion of the DGI sample likely comes from outsourcing and/or body-shopping firms. This is also confirmed by DGI (appendix table 30 – group D); their results are not significant for industries other than "professional, scientific, and technical services."

The sample in DGI consists of all firms that hire H-1B workers, including outsourcing firms such as Infosys, Wipro, Tata Consultancy Services, and Cognizent, which provide low-end temporary support services. Because our sample is matched on Compustat North America, we automatically exclude the outsourcing firms, most of which are primarily American depository receipts (ADR) or foreign stock traded on a U.S. exchange, based in India. When DGI separate out outsourcing or temporary support services industries, their "point estimates" are smaller and insignificant for these industries as well as for the rest of their sample.

These differences in industry classification are reflected in the innovation outcome of our respective samples. In our sample, the firms on average have 27 patents and the standard deviation of patents is 29. Our innovation outcome numbers, either raw or scaled by R&D investment, are consistent with the financial economics literature (Chava et al. (2015)). The average firms in the DGI sample, on the other hand, have 4.5 patents on average and the standard deviation in the number of patents is 56.0, showing a very large number of outliers. For firms with fewer than 30 employees, where the DGI results are the strongest, the average number of patents and the standard deviation in the number of patents is 0.23 and 8.59 respectively. The innovative ability of the DGI sample firms is far lower than that of our control group of non H-1B dependent firms with 9 patents on average (with 19 standard deviation) . The H-1B-dependent (control) firms in our pooled sample have a patenting rate of 85% (65%) in comparison with 9% in the DGI sample,

[38] DGI also provide regression estimates that firms that file petitions on the lottery day had a higher likelihood (by 1%) of patenting in year -1, and are bigger (by 10%), than non-lottery day firms, but the results are not statistically significant at the conventional level. In addition, the patenting rate measured in one specific year, especially around the year of the immigration policy shock, is not necessarily evidence of superior innovative ability.

and the average annual patenting rate is 64% (40%) in our sample, in comparison with 5% in the DGI sample.

Because of these huge difference in the innovation outcome, we conclude that the two sets of samples used by DGI and in our study represent very different types of firms. In general, based on the standard deviation numbers, the DGI sample is also likely to have far more outliers than our sample which has undergone the standard winsorizing procedure to eliminate outliers.

The firms in our sample, on average, have 37,100 employees and are fifteen times larger than the DGI firms, which have 1,800 employees on average. Even among the DGI sample firms, most of their results are significant for the smallest firms with fewer than 10 or fewer than 30 employees.

Given all these differences in firm size, industry distribution, innovative abilities, and potentially R&D investment (DGI do not analyze capital input to innovation) of the two different samples, it is not surprising that our conclusions are very different. Any policy prescription related to skilled immigration needs to take these differences into account.

Finally, DGI report inconclusive results (pg. 52 and appendix table 31) and write that they "find no evidence that H-1B workers crowd out citizen workers" and that "new H-1Bs do at least partially crowd out other non-citizens." If we believe the argument in Tervio (2008) that certain skills and quality of human capital or talent can only be assessed by observing an employee on the job, a logical conclusion is that non-incumbent H-1B workers will continue to partially crowd out the below-median (based on observed performance level) incumbent H-1B workers from earlier cohorts. Whether some H-1B workers go on to become citizens in the future is less relevant for the discussion. It is entirely likely that those incumbent H-1B workers who demonstrate on-the-job skills and talents that are superior to the rest of the H-1B and host-country workers will eventually be sponsored by their employers to become permanent residents and/or citizens.

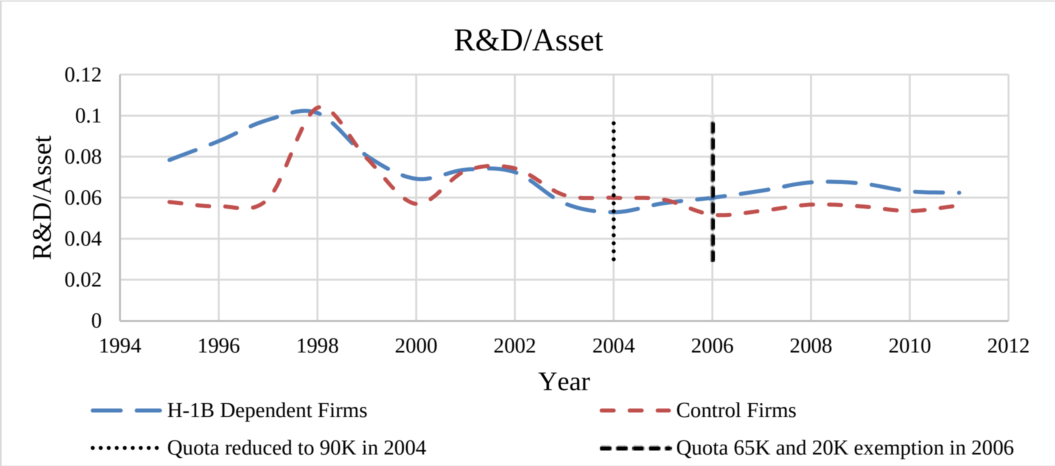

Figure IA.1: Expenditures on Research and Development (R&D) by the H-1B-Dependent (Treated) and Non-dependent (Control) Firms

This figure presents the research and development (R&D) expenditures ($million in 2001 real U.S. dollars) normalized by total assets ($million in 2001 real U.S. dollars) for H-1B-dependent (treated) firms and non-dependent (control) firms for the period 1995 to 2011.

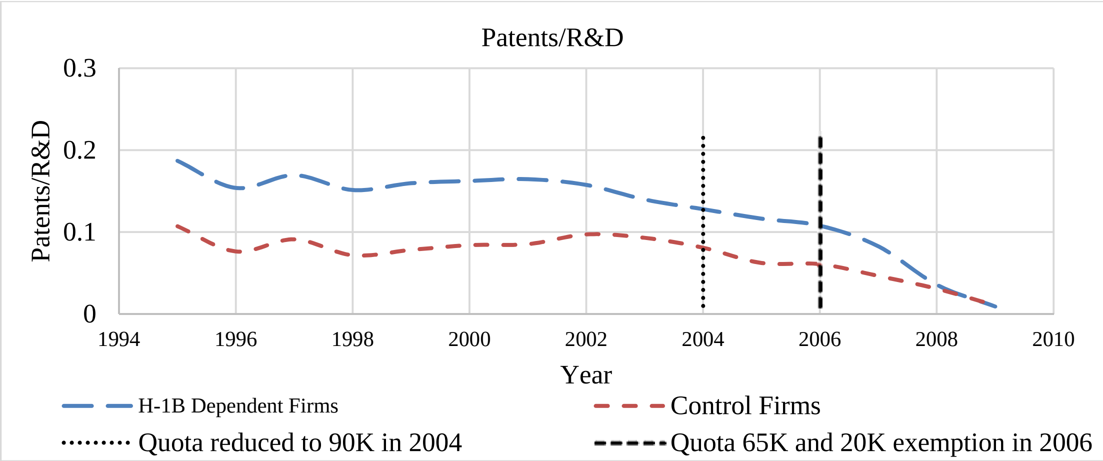

Figure IA.2: Number of Patents per Unit of Research and Development (R&D) Expenditure ($100 million – 2001 real U.S. dollars) for the H-1B-Dependent (Treated) and Non-dependent (Control) Firms.

This figure displays the average number of patents per unit of research and development (R&D) expenditure ($100 million in 2001 real U.S. dollars) for the H-1B-dependent (treated) firms and non-dependent (control) firms for the period 1995 to 2009.

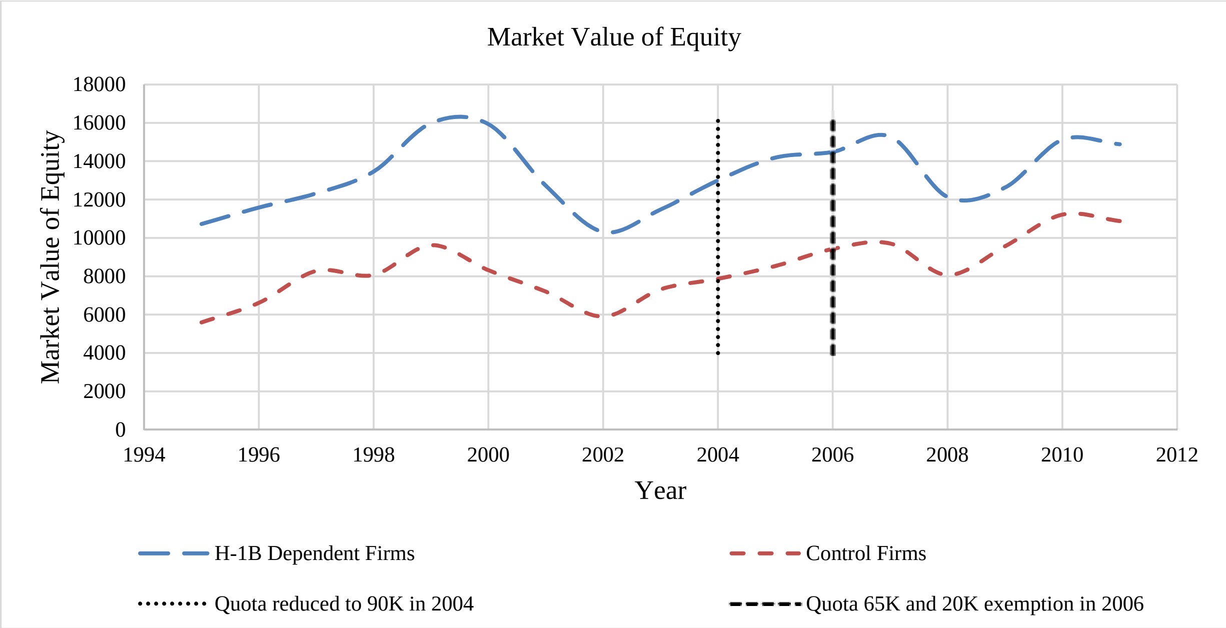

Figure IA.3: Market Value of Equity ($ million) for the H-1B Dependent (Treated) and Non-dependent (Control) Firms for the years 1995-2011.

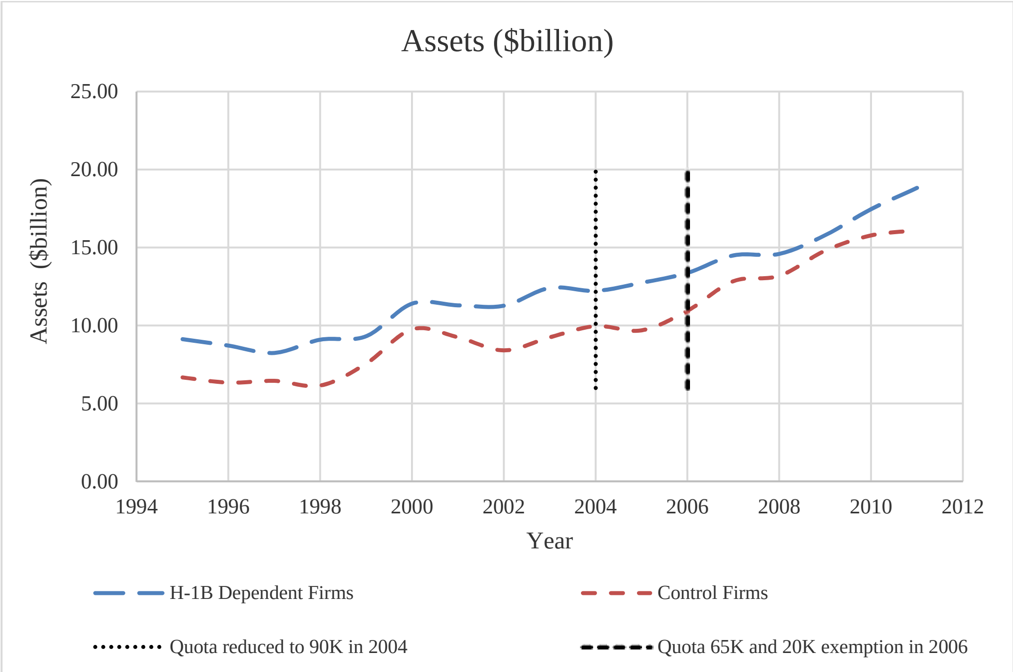

Figure IA.4: Assets ($billion) for the H-1B Dependent (Treated) and Non-dependent (Control) Firms for the years 1995-2011.

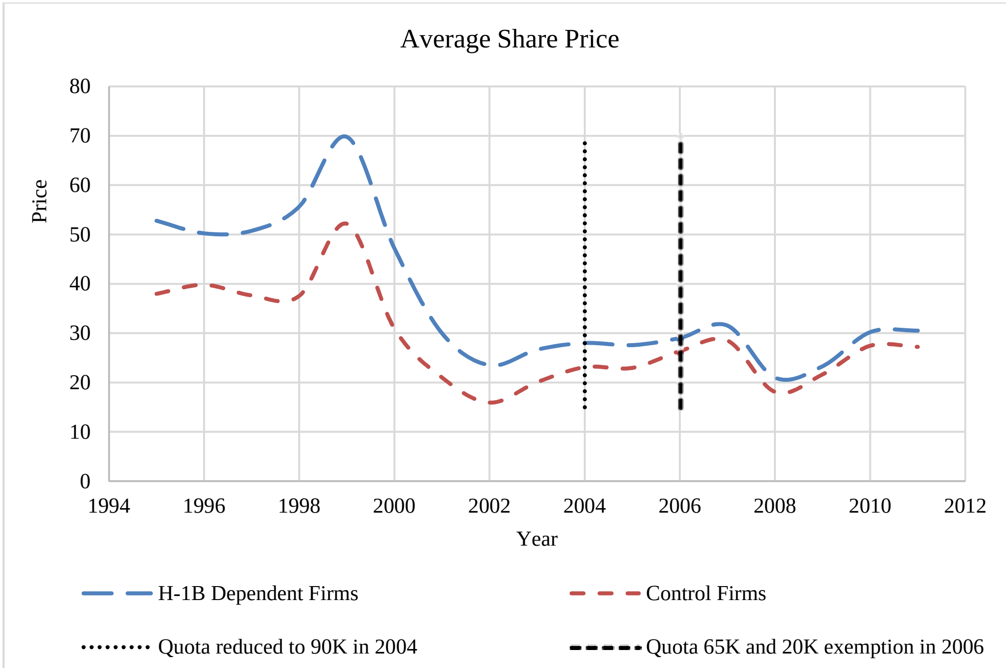

Figure IA.5: Average Share Price for the H-1B Dependent (Treated) and Non-dependent (Control) Firms for the years 1995-2011.

Internet Appendix - Table A.1: Propensity-Score Matching: Before and After Match

This table reports the parameter estimates from the probit model used to generate the propensity scores for the treatment and control groups. The dependent variable equals one if the firm is an H-1B-dependent firm (treated) and zero if it is a non-H-1B-dependent firm (control). A firm is identified as H-1B dependent (treated) if a firm hires at least 20 H-1B employees in the years 2002 and 2003 (prior to policy shock in 2004). H-1B-dependent firms are matched with a control group using the propensity-score matching method for the year 2001(pre-sample year) based on: firm size; leverage; market-to-book ratio; selling, general, and administrative expense (SG&A); research and development (R&D) expenditures; and number of patents over R&D within the same 4-digit SIC industries. In the pre-match column 1, the parameter estimates of the probit model are performed on the entire sample, prior to matching. In the post-match column 2, the parameter estimates of the probit model are obtained on the subsample of matched treated and control observations, after matching. Industry- and year- fixed-effects are included in both models. In columns 1 and 2 the t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Probit regression	
	Unmatched	Matched
	(1)	(2)
Ln(Assets)	0.268*** (2.84)	0.053 (0.41)
Leverage	-0.571* (-1.67)	-0.323 (-0.68)
Market-to-Book	0.016* (1.62)	0.009 (0.81)
Ln(SG&A)	0.466*** (4.12)	0.296** (1.99)
Ln(R&D)	0.045 (0.87)	-0.003 (-0.05)
Patent/R&D	0.025 (1.42)	0.021 (1.01)
Industry FE	Yes	Yes
Observations	2465	378
Pseudo R^2	0.52	0.11

Internet Appendix - Table A.2: Alternative Explanation: Internet Boom and Bust and Patents and Citations: Univariate Evidence

Patents					
		H-1B Dependent Firms	Control Firms	1st Diff	2nd Diff (Diff-in-Diff)
	Pre-shock (1999-2001)	29.67	8.39	21.29 *** (14.35)	
	Post-shock (2002-2004)	30.17	10.72	19.45 *** (12.59)	-1.83 (0.39)

Citations					
		H-1B Dependent Firms	Control Firms	1st Diff	2nd Diff (Diff-in-Diff)
	Pre-shock (1999-2001)	26.72	8.07	18.65 *** (15.30)	
	Post-shock (2002-2004)	25.59	8.80	16.79 *** (13.22)	-1.86 (0.29)