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Working Paper

09-005

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December 2008
HBS Working Paper 09-005*

Abstract

This study evaluates the impact of high-skilled immigrants on US technology formation. Specifically, we use reduced-form specifications that exploit large changes in the H-1B visa program. Fluctuations in H-1B admissions levels significantly influence the rate of Indian and Chinese patenting in cities and firms dependent upon the program relative to their peers. Most specifications find weak crowding-in effects or no effect at all for native patenting. Total invention increases with higher admission levels primarily through the direct contributions of ethnic inventors.

JEL Classification: F15, F22, J44, J61, O31.

Key Words: Innovation, Research and Development, Patents, Scientists, Engineers, Inventors, H-1B, Immigration, Ethnicity, India, China, Endogenous Growth.

*Comments are appreciated and can be sent to wkerr@hbs.edu and wlincoln@umich.edu. We thank Sarah Rahman for excellent research assistance. We thank seminar participants at ERSA, Harvard, Michigan, MIT Sloan, NBER Innovation Policy and the Economy, NBER Labor Studies, and NBER Productivity for helpful suggestions; we especially thank Lindsey Lowell and Debbie Strumsky for data assistance and Ajay Agrawal, David Autor, Charlie Brown, Brendan Epstein, Richard Freeman, Jeff Furman, Jennifer Hunt, Sari Kerr, Miles Kimball, Josh Lerner, Jim Levinsohn, Guy Michaels, Matt Mitchell, Ramana Nanda, and Jeff Smith for their insights. This research is supported by the Innovation Policy and the Economy group, Kauffman Foundation, Harvard Business School, the National Science Foundation, and the MIT George Schultz Fund.

1 Introduction

The H-1B visa program governs most admissions of temporary immigrants into the US for employment in patenting-related fields. This program has become a point of significant controversy in the public debate over immigration, with proponents and detractors at odds over how important H-1B admission levels are for US technology advancement and whether native US workers are being displaced by immigrants. In this study we quantify the impact of changes in H-1B admission levels on the pace and character of US invention over the 1995-2006 period. We hope that this assessment aids policy makers and business leaders by informing their current discussions about appropriate admission rates in the future. Of more general interest, the variations induced by changes in H-1B admissions are an attractive laboratory for studying whether immigrant scientists and engineers (SEs) crowd-in or crowd-out native SE workers. Identifying this native response is important for assessing the extent to which aggregate US invention is promoted by more flexible high-skilled immigration policies.

The link between immigration policy and new innovation may appear tenuous at first, but immigrant SEs are central to US technology formation and commercialization. In terms of levels, immigrants represented 24% and 47% of the US SE workforce with bachelors and doctorate educations in the 2000 Census, respectively. This contribution was significantly higher than the 12% share of immigrants in the US working population. The growth of this importance in recent years is even more striking. From the Current Population Survey (CPS), we estimate an overall increase in the US SE labor force of 475k workers from 1995 to 2006. The net increase in immigrant SEs during these twelve years was 319k workers — 67% of the total. Looking even further, the number of non-citizen SE immigrants increased by 144k, or 30% of the total SE increase, and this simple statistic abstracts from immigrants who obtained citizenship during the period.[1]

Greater inflows of educated immigrants do not necessarily increase the pace of US innovation, however. If there are large crowding-out effects, growth in immigrant SEs will displace native SE workers and the total growth of innovation could be unaffected. To disentangle these issues, it is possible to exploit variation across dimensions like geography and industry. Establishing this variation is quite challenging with standard data sources, however. Partial correlations also do not identify causal relationships in this context due to the endogeneity of immigrant location decisions. For example, we show below that growth in immigrant SEs is correlated

[1]The details of the CPS calculations are described in Section 3. Papers describing the contributions of immigrants to SE include Stephan and Levin (2001), Burton and Wang (1999), Johnson (1998, 2001), Streeter (1997), Saxenian (2002a,b), Matloff (2003, 2004), Miano (2005, 2008), Lowell and Christian (2000), Borjas (2005, 2006), Wadhwa et al. (2007), Chellaraj et al. (2008), Kerr (2008a,b), Peri (2007), and Hunt and Gauthier-Loiselle (2008). Freeman (2005, 2006) surveys global labor flows and discusses their deep scientific impacts. General surveys of immigration include Borjas (1994), Friedberg and Hunt (1995), and Kerr and Kerr (2008).

with contemporaneous growth in native SEs across cities and states. A causal interpretation of this correlation would suggest that strong crowding-in effects exist. An alternative explanation, however, would be that immigrant and native SEs are simultaneously attracted to cities and states with rapidly expanding technology opportunities and SE labor demand. Alternatively, reverse causality may hold, where strong growth in native innovation attracts immigrants directly.

To bring identification to this question, we exploit large changes in the H-1B worker population over the 1995-2006 period. The national cap on new H-1B admissions fluctuated substantially over these years, ranging from a low of 65k new workers a year to a high of 195k. SE and computer-related occupations account for approximately 60% of H-1B admissions, and changes in the H-1B population are responsible for most of the non-citizen immigrant SE workforce increase noted above.

Our main estimations consider differences across US cities in the extent to which they relied on the H-1B program. Specifically, we characterize differences in patenting behavior between dependent cities and their less dependent peers resulting from shifts in H-1B admission levels. Our analyses primarily exploit a unique data set of probable inventor ethnicities for all US patents. These ethnicities are identified through inventors' names — for example, inventors with the last names Gupta or Desai are more likely to be Indian than they are to be Vietnamese. The detail of these micro-records covers the universe of US domestic invention and affords analyses that are not possible with other data sets.

The city-level analysis divides 281 US cities into five quintiles based upon their dependency on the H-1B program. Our empirical specifications then compare how patenting growth in the top three quintiles of the distribution responded to shifts in H-1B admissions relative to patenting growth in the bottom two quintiles. This framework allows for non-linear effects across dependency levels due to policy reforms. In addition to providing a richer account of treatment effects, this flexibility is important given that political economy forces may influence the cap on admissions set by the federal government. We argue below that admission levels are plausibly exogenous for the second and third quintiles of the dependency distribution, even if the results from the upper quintile of 57 cities may contain some bias.

Our first finding is that increases in H-1B admissions substantially increased rates of Indian and Chinese invention in dependent cities relative to their peers. In the base specifications, a 10% growth in the H-1B population increased Indian and Chinese invention by 6%-12% in the most dependent quintile of cities relative to the bottom two quintiles. Just as importantly, the relative rates of Indian and Chinese invention grew by 2%-7% in the second and third quintiles. These differences are economically important and statistically different from responses in the reference category. Responses are also weaker for other non-English inventor groups, which is to be expected given the H-1B program's primary pull from India and China for SE workers.

Turning to crowding-in versus crowding-out effects, positive elasticities typically exist for inventors with English names in these estimations as well. This suggests positive effects for natives, as English inventors account for 72% of all inventors in our sample. These elasticities, however, are much smaller than those for other ethnicities and are often not statistically different from zero. In the baseline specification, a 10% growth in the H-1B population increases English invention by 0%-1% in the most dependent quintile relative to the least. This suggests that natives are not likely being crowded-out in large numbers by higher H-1B admissions. The elasticities also indicate that crowding-in effects are small to the extent that they exist. Combining elasticities with inventor group sizes, crowding-in contributions would be about half of immigrants' direct contributions in the 1% scenario, whereas all technology growth would come from ethnic inventors themselves in the 0% scenario. Total invention is estimated to increase by 0%-2% in the short-run.

We test the robustness of these city-level findings in several ways. We first examine different specifications that include technology trends, state-year fixed effects, dropping highly dependent cities, and dropping the patenting of a large group of the most H-1B dependent firms. We also show that our results for US cities are not reflected in a placebo experiment involving shifts in ethnic invention among Canadian cities. We further estimate a dynamic specification and confirm our results through the CPS. Across the different specifications, Indian and Chinese patenting are consistently shown to be dependent upon the H-1B program, English invention is typically weakly correlated, and the results for other ethnicities fall in between. The majority of our estimates suggest that native invention is either not affected by the H-1B program in the aggregate or that a weak crowding-in effect exists.

Our final analysis considers variation in patenting within firms. High-tech industry executives often argue that their firms are especially prone to fluctuations in H-1B admissions. We create a panel of the most H-1B dependent firms to test this claim. Higher H-1B admissions are associated with stronger increases in Indian invention in highly dependent computer-oriented firms (e.g., Microsoft, Oracle), relative to both less dependent computer-oriented firms and to highly dependent firms in other sectors. On the other hand, growth in English invention is comparable across sectors for very dependent firms, with small increases relative to less dependent firms.

In a broader context, we view this paper as a building block for describing the supply side of innovation. Rivera-Batiz and Romer (1991) and others have shown how the sharing of ideas across countries can lead to higher levels of innovation in endogenous growth models. We believe that these effects can be large with high-skilled immigration, especially when the knowledge needed to create new ideas is tacit. We also suspect that there may be a more subtle mechanism at work. The demand side of the economy governs the pace of innovation in most models of endogenous growth; larger markets encourage greater entrepreneurial innovation due to profit incentives. To facilitate this process, labor adjusts across research and manufacturing sectors to equate wages and generate balanced growth. Shocking these economies with high-skilled labor inflows does not increase innovation except trivially through larger economy size.[2]

However, there are often significant adjustment costs when workers move across occupations and sectors, particularly in moving into research-oriented occupations. Ryoo and Rosen (2004) and others have documented the significant costs and "time to build" inherent in increasing the supply of ideas workers, particularly in SE. Shortages of sufficiently trained labor may exist even if forward-looking workers are rationally responding to incentives. These costs and slower adjustments open up the possibility for supply shocks to US innovation through shifts in immigration policy. Indeed, public debates about the H-1B visa often turn on whether a shortage of high-skilled workers exists or not.

Recent work has begun to investigate these effects, generally finding a positive relationship between immigration and US inventive activity. Peri (2007) and Hunt and Gauthier-Loiselle (2008) explore long-run relationships between immigration levels and patenting rates using state-decade variation. The latter study in particular finds substantial crowding-in effects, such that a one percentage point increase in US immigrant college graduates raises patents per capita by about 15%. Chellaraj et al. (2008) study the contribution of international graduate students and skilled immigration for US patenting using time-series approaches. These authors estimate that crowding-in effects from foreign graduate students in the US are equal to half of the direct contributions of immigrants. In contrast to these studies, Borjas (2005, 2006) finds that natives are crowded-out from graduate school enrollments by foreign students, especially in the most elite institutions, and suffer lower wages after graduation due to the increased labor supply. This disagreement in the academic literature is reflected in the public debate over high-skilled immigration and the H-1B visa in particular.

Our paper contributes to this research through its measurement of ethnic patenting and the use of H-1B policy changes for the identification of immigrant SE inflows. Our paper is the first large-scale description of ethnic invention within firms and the first study to characterize the firm-level linkage of immigration and innovation. Understanding the micro-economic linkages governing this process is important as immigration policies influence firms, universities, and other institutions differently. The small crowding-in effects that we typically measure fall in between the results of prior academic work and the effects suggested in the public debate.[3]

[2] See, for example, the standard endogenous growth frameworks in Romer (1986, 1990), Jones (1995), and Barro and Sala-i-Martin (1995). See also Acemoglu and Linn (2004) and Furman et al. (2002).

[3] In a related paper, Foley and Kerr (2008) examine the firm-level link between immigration and FDI.

The next section of this paper describes the ethnic patenting data that we exploit in this study. Section 3 introduces the H-1B program and provides some basic calculations about the degree to which the H-1B program can impact US invention rates. Sections 4 and 5 present the city and firm analyses, respectively. The final section concludes.

2 US Ethnic Invention

We begin by describing our ethnic inventor data set and then proceed with simple panel estimations of the relationship between ethnic inventors and English inventors. These correlations provide a background for our study of the H-1B program, which is described in the next section.

2.1 Ethnic Patenting Data Set

We quantify ethnic technology development in the US through the individual records of all patents granted by the United States Patent and Trademark Office (USPTO) from January 1975 to May 2008. Each patent record provides information about the invention (e.g., technology classification, citations of prior art) and the inventors submitting the application (e.g., name, city). Hall et al. (2001) provide extensive details about this data set. USPTO patents must list at least one inventor, and multiple inventors are often listed. The data are extensive, with 8 million inventors associated with 4.5 million granted patents during this period.

To estimate ethnicities, a commercial database of ethnic first names and surnames is mapped into inventor records. Kerr (2007) documents name-matching algorithms, lists frequent ethnic names, and provides extensive descriptive statistics. The match rate is 98% for domestic inventors, and the process affords the distinction of nine ethnicities: Chinese, English, European, Hispanic, Indian, Japanese, Korean, Russian, and Vietnamese. Kerr (2007) also discusses quality assurance exercises performed. One such exercise regards the composition of foreign patents registered with the USPTO. We are able to assign ethnicities to 98% of foreign records, and we find that the resulting estimated inventor compositions are quite reasonable. For example, 85% to 90% of inventors filing from India and China are classified as ethnically Indian and Chinese. This is in line with what we would expect, as native shares should be less than 100% due to the role that foreign inventors play in these countries. Since our regressions mostly employ ethnic patenting as a dependent variable, remaining measurement error in inventor ethnicities will not substantively influence the consistency of our estimates.

Table 1 describes the 1975-2004 US sample, while Figure 1 illustrates the evolving ethnic contribution to US technology development as a percentage of patents granted by the USPTO.

These statistics are just for inventors residing in the US. The trends demonstrate a growing ethnic contribution to US technological development, especially among Indian and Chinese scientists. Ethnic inventors are more concentrated in high-tech industries like computers and pharmaceuticals and in gateway cities relatively closer to their home countries (e.g., Chinese in San Francisco, Europeans in New York, and Hispanics in Miami). The final three rows of Table 1 demonstrate a close correspondence between the estimated mean ethnic composition during the period with the country-of-birth composition of the US SE workforce in the 1990 Census.

The appendix lists major US cities and their shares of total patenting, non-English patenting, and Indian and Chinese patenting.[4] We define cities through 281 Metropolitan Statistical Areas. Not surprisingly, total patenting shares are highly correlated with city size, with the three largest shares of US domestic patenting for 1995-2004 found in San Francisco (12%), New York (7%), and Los Angeles (6%). More interestingly, non-English patenting is more concentrated than general innovation. The 1995-2004 non-English patent shares of San Francisco, New York, and Los Angeles are 19%, 10%, and 8%, respectively. Similarly, 81% of non-English invention occurs in the top 47 patenting cities listed in the appendix, compared to 73% of total patenting. Indian and Chinese invention is even further agglomerated. San Francisco shows exceptional growth from an 8% share of total US Indian and Chinese patenting in 1975-1984 to 25% in 1995-2004, while the combined shares of New York and Chicago decline from 22% to 13%.[5]

Figures 2 and 3 provide a more detailed view of Indian and Chinese contributions for different technology sectors. These two ethnicities are more concentrated in high-tech sectors than in traditional fields, and their 1990s growth as a share of US innovation is remarkable. A large portion of this growth is due to the rapid economic development of these countries and their greater SE integration with the US. Similarly, sustained US economic growth during the period likely made America more attractive as a host country. The US Immigration Act of 1990 also facilitated greater permanent immigration of SE workers from these countries in the early 1990s (e.g., Kerr 2008a).

Figure 3 exhibits an interesting downturn in the Indian share of computer-related invention after 2000, which includes software patents. This shift from the strong growth in the 1990s is striking and may reflect more restrictive US immigration policies. Many factors contribute, however, such as the high-tech recession and the increasing attractiveness of foreign opportunities like Bangalore. Accordingly, our estimations control for these aggregate trends through year fixed effects. Nonetheless, macro trends document substantial shifts in ethnic invention patterns over the last decade.

[4] The appendix contains both extended empirical results and details about the data set development. It is available at http://www.people.hbs.edu/wkerr/.

[5] Agrawal et al. (2007a,b), Mandorff (2007), and Kerr (2008b) further describe issues in ethnic agglomeration. The former studies are particularly interesting in their theoretical depiction of the substitutability between ethnic social ties and geographic proximity. Differences between a social planner's optimal distribution of ethnic members, and what the inventors themselves would choose, can emerge.

The base data contain information on all patents granted from January 1975 to May 2008. Application years of patents, however, provide the best description of when innovative research is being undertaken due to the existence of substantial and uneven lags in USPTO reviews. Accordingly, annual descriptions employed in this study are measured through patent application years. This standard approach leads to sample attrition after 2004 as many applications have not been processed for approval at the time of writing. To compensate for this, we also employ a data set of 1.8m published patent applications, which the USPTO began releasing in 2000. Our preferred data set combines the patent grants and applications data, removing multiple records for the same patent. This union yields more consistent sample sizes in later years. We also consider estimations that use grants data only in robustness checks.

While the ethnic patenting data provide a tractable platform for examining immigration and innovation, it is important to discuss explicitly the data's limitations and the extent to which these issues influence our analysis. First, our approach does not distinguish between foreign-born inventors in the US and later generations working in SE. The panel econometrics employed, however, identify off of relative changes in ethnic inventor populations. For Indian and Chinese inventors, these changes are mainly due to new immigration or school-to-work transitions that require a visa, substantially weakening this overall concern. On a similar note, we study crowding-in and crowding-out through inventors with English names. In addition to capturing effects on US natives, inventors with English names also reflect some immigration from the UK, Canada, etc. The magnitudes of H-1B-related inflows from English ethnicity countries suggest that this second factor is very small. Temporary workers from Canada and the UK account for about 10k new H-1B workers annually over the 2000-2005 period, a small number compared to a native SE workforce of more than 2.5m. Our robustness checks using the CPS further allay both of these concerns.

2.2 Correlations of Ethnic Invention and English Invention

Before discussing the H-1B program, it is useful to describe correlations in ethnic inventor growth across cities. This exercise has descriptive value, and it introduces questions about endogeneity that we address in our reduced-form analysis. We estimate for city c and year t,

$$\ln(PAT_{c,t}^{Dep}) = \phi_c + \eta_t + \beta \cdot \ln(PAT_{c,t}^{Ind,Chn}) + \epsilon_{c,t}, \quad (1)$$

where ϕ_c and η_t are vectors of city and year fixed effects, respectively. Our dependent variables are the log of the total number of patents in a city-year and the log of the number of patents by English inventors. Our key explanatory variable is the log of the total number of patents by Indian and Chinese inventors. We focus on patenting by these two ethnicities here because they play a disproportionate role in the H-1B visa program.

Table 2 documents the partial correlations. Estimations consider 281 cities over the years 1995-2006 for a total of 3372 observations. We discount multiple inventors on a patent such that each patent receives the same weight. We only include patents where all of the inventors work in the US for this exercise and for our other domestic analyses. Regressions are unweighted and cluster standard errors by city to address the serial correlation concerns of Bertrand et al. (2004) when exploiting high-frequency variation.

Panel A employs English ethnicity patenting as the dependent variable, while Panel B considers total patenting. The upper left coefficient in Column 1 documents a 0.14 elasticity between city-level growth in Indian and Chinese patenting and the growth of English patenting. To put this in perspective, this suggests that a 10% increase in Indian and Chinese patenting correlates with a 1.4% increase in English patenting. This partial correlation should not be interpreted as a causal parameter due to potential omitted variable biases and reverse causality. The strong and positive effect, however, does provide some prima facie evidence against very strong crowding-out effects.

Columns 2-5 provide several robustness checks on these correlation estimates. We first introduce a measure of the expected patenting in each city due to aggregate technology trends and the pre-period composition of each city's invention. Section 4 contains a detailed description of how we construct these technology trends. The results from this estimation indicate that changes in national technology trends or USPTO grant rates are not responsible for the estimated positive correlations. Our further analyses in Columns 3-5 retain this expected patenting measure. Column 3 shows that the elasticity estimates are robust to including state-year fixed effects that account for regional differences in city growth. Finally, Columns 4 and 5 provide some simple checks on the composition of the sample. Column 4 weights the regression by the 1994 city populations, while Column 5 drops the top 20% of cities in terms of 1994 population. The stability of the elasticities across these two permutations indicates that correlations are not due to small outliers or exclusive to major population centers only.

Panel B reports elasticities for total invention. These patenting correlations are naturally stronger than Panel A's English ethnicity correlations, as total patenting includes the direct contributions of ethnic inventors as well. Significant and positive results are found across all specifications. To see what these estimates mean for US invention generally, we consider a simple adding-up exercise. Indian and Chinese inventors account for roughly 13% of US domestic patents over 1995-2006, compared with a 72% share for English inventors. A hypothetical 10% increase in Indian and Chinese invention directly contributes about 1.3% to total invention growth (i.e., 10% x 13%). Briefly assuming a causal crowding-in effect, the concomitant 1.4% increase in English invention would also contribute 1.0% to total invention (i.e., 1.4% x 72%) due to the larger inventor population over which the 0.14 elasticity is applied. This would suggest an indirect effect equal to about three-quarters of the direct contribution. These estimates are approximate and do not add up directly to the estimated 2.1%, as we do not consider other factors such as the patenting of other ethnicities and spatial differences that exist in ethnic inventor populations. We present them to highlight the fact that even small elasticities for English inventors can have important economic effects due to the large inventor population over which they are estimated.

The appendix extends this analysis. We first estimate specification (1) individually for the five largest ethnic patenting groups: Indian, Chinese, European, Hispanic, and Russian. Univariate elasticities of 0.11 are measured between English patenting growth and Indian or Chinese patenting growth. European and Hispanic elasticities are larger at 0.15 and 0.13, respectively, while the Russian univariate correlation is weaker at 0.08. Growth in European and Hispanic patenting, which are not treated in the simple estimates of Table 2, are more correlated with English invention growth than Indian and Chinese patenting. This could be due to two factors. Table 1 shows that European and Hispanic inventors are more concentrated in technology fields and cities common to English inventors. The second factor, which relates to a limitation of our methodology, is that European and Hispanic names overlap more with English names than they do with names of Asian ethnicities.

These two traits are important for interpreting our city-level analysis of the H-1B program. Analyses that trace English invention responses to local shocks in Indian and Chinese invention stemming from changes in H-1B admissions are less likely to be confounded by omitted variables or name overlaps than similar European-based immigration shocks. In this sense, the H-1B program is a relatively clean laboratory for quantifying crowding-in or crowding-out effects. Treatment effects will, however, be determined in sectors and cities where English inventors are less common (but typically still the majority). Measured effects due to Indian and Chinese shocks may underestimate or overestimate the latent treatment effects for other immigrant groups that are naturally closer to English invention.

Additional estimations confirm that these results hold individually for granted patents and patent applications. Second, while all city-year cells have some patenting, smaller cities can lack Indian or Chinese patenting. Estimations recode counts of less than one ethnic patent for a given city-year observation to be equal to one ethnic patent. We do so under the claim that is not meaningful to distinguish between zero and one Indian or Chinese patent for a city. This is merely done to maintain consistent sample sizes and elasticity estimates strengthen only slightly when we instead drop zero-valued cells. The results are further robust to dropping the West Coast, looking within firms, or employing a first-differenced version of equation (1).[6]

[6] The efficiency of a first-differenced form versus the levels specification turns on whether the error term is autoregressive. If autoregressive deviations are substantial, the first-differenced form is preferred; a unit-root error is fully corrected. If there is no serial correlation, however, first differencing introduces a moving-average error

3 H-1B Visa Program

This section overviews the H-1B visa program and provides a back-of-the-envelope analysis of how large its impact for US SE can be. We focus on SE workers as they produce the large majority of patented innovations. This description concentrates on the major features of the H-1B program relevant for our analysis, and we refer interested readers to Lowell and Christian (2000), Lowell (2000), Matloff (2003), and Kirkegaard (2005) for additional details. Facchini et al. (2008) overview other temporary immigration categories.

3.1 Overview of the H-1B Visa Program

The H-1B visa is a temporary immigration category that allows US employers to seek short-term help from skilled foreigners in "specialty occupations." These occupations are defined as those requiring the theoretical and practical application of a specialized body of knowledge (e.g., engineering, accounting); virtually all successful H-1B applicants have a bachelors education or above. The visa is used especially for SE and computer-related occupations, which account for roughly 60% of successful applications. Approximately 40% and 10% of H-1B recipients over 2000-2005 came from India and China, respectively. Shares for other countries are all less than 5%; almost all are less than 3%.

The sponsoring firm is responsible for filing the H-1B application and must specify an individual candidate. The employer-employee match must therefore be made before the application is submitted. Different employers can simultaneously seek visas for the same prospective employee, although firms generally make applications only on behalf of committed workers due to the time and legal fees involved. The application fee for a firm with 26 or more full-time employees was $2,320 in 2008.

Workers are tied to their sponsoring firm, although some very recent changes have increased visa portability. Firms can petition for permanent residency (i.e., a green card) on behalf of the worker. If permanent residency is not obtained, the H-1B worker must leave the US at the end of the visa period for at least one year before applying again. Firms are also required to pay the higher of (1) the prevailing wage in the firm for the position to be filled or (2) the prevailing wage for the occupation in the area of intended employment. These restrictions were designed to prevent H-1B employers from abusing their relationships with foreign workers and to protect the wages of domestic workers.

component. Estimations of the autoregressive error parameter in the levels specification (1) find serial correlations of 0.2; the serial correlation of -0.4 is stronger in the first-differenced form. The levels specification is thus our preferred estimation technique but we report the first-differenced form as a robustness check. These estimations find marginally weaker correlations for the English ethnicity and similar correlations for total patenting.

Kirkegaard (2005) provides evidence that firms often use the H-1B program to keep wage costs down but are largely in accordance with the law in terms of the wages that they offer to their visa-holding workers. Lowell (2001) and Zavodny (2003) find limited evidence that the H-1B program influences native wages. In contrast, Matloff (2003, 2004) discusses abuses of the system, and Miano (2005) debates whether the prevailing wage requirement is effectual. A 2008 United States Citizenship and Immigration Services (USCIS, the successor to the Immigration and Naturalization Service) study finds recent evidence of fraud or technical violations in 20% of sampled H-1B cases, with incident rates especially high among small employers and human resources firms.

Since the Immigration Act of 1990, there has been an annual cap on the number of H-1B visas that can be issued. The cap governs new H-1B visa issuances only; renewals for the second three-year term are exempt and the maximum length of stay on an H-1B visa is thus six years. Unlike permanent immigration, immediate family members of the H-1B worker do not count towards the visa cap. These family members are, however, restricted from working unless they otherwise obtain an appropriate work visa. Free trade agreements require that 1,400 and 5,400 of the visas be reserved for citizens of Chile and Singapore, respectively. These special allotments are often under-utilized, however, and the excess capacity is returned to the general pool.

While most of the other aspects of the H-1B program have remained constant over the past 15 years, the cap has fluctuated significantly. The largest amount of controversy about the H-1B program focuses on this cap. Indeed, a search of Lexis-Nexis finds more than three thousand news articles about the visa from 1995-2006. Prominent peaks in media attention are evident during legislative debates about raising or lowering the cap. Executives of high-tech firms often argue that lower H-1B admissions in recent years have starved their firms of needed talent and hindered US innovation. They suggest that higher admissions are necessary to keep US businesses competitive, to spur innovation and growth, and to keep firms from shifting their operations abroad. Detractors, on the other hand, argue that the H-1B program displaces American workers, lowers wages, and discourages on-the-job training (e.g., Matloff 2003, 2004).[7]

Figure 4 plots the evolution of the numerical cap. The 65k cap was not binding in the early 1990s but became so by the middle of the decade. Two pieces of legislation, the American Competitiveness and Workforce Improvement Act of 1998 and the American Competitiveness in the Twenty-First Century Act of 2000, sharply increased the cap over the next five years to

[7] Bill Gates' March 2007 Congressional Testimony illustrates the first perspective: "I personally witness the ill effects of these (H-1B) policies on an almost daily basis at Microsoft ... The current base cap of 65,000 is arbitrarily set and bears no relation to US industry's demand for skilled professionals."

Milton Friedman's July 2002 *ComputerWorld* interview, on the other hand, illustrates the second perspective: "There is no doubt that the (H-1B) program is a benefit to their employers, enabling them to get workers at a lower wage, and to that extent, it is a subsidy."

195k visas. The language contained in the 1998 legislation argued that "American companies today are engaged in fierce competition in global markets" and "are faced with severe high-skill labor shortages that threaten their competitiveness."[8] These short-term increases were allowed to expire during the US' high-tech downturn, when visa demand fell short of the cap. The cap returned to the 65k level in 2004 and became binding again, despite being subsequently raised by 20k through an "advanced degree" exemption.

The two closest temporary worker visas to the H-1B are the L-1 and TN visas. Neither of these visa categories is a particularly good substitute for the H-1B. The L-1 is issued to multinationals in order to bring in managers or employees with "specialized knowledge" that have worked for the firm abroad for at least one year. The TN visa was established under NAFTA and allows citizens from Mexico and Canada to work in the US in certain high-skilled occupations. Both of these programs are less than 10% of the size of the H-1B program for high-tech workers during the 1995-2006 period and contain institutional features that limit firms' ability to use them to circumvent the H-1B quota. Neither visa category shows substantial increases after the H-1B cap was dramatically reduced in 2004, and the Department of Homeland Security has concluded that limited substitution exists across the H-1B and L-1 visas. The appendix discusses these other temporary visas further.

Prior research on the H-1B visa program is sparse and mostly descriptive due to data limitations. Indeed, these data constraints significantly shape our empirical approach discussed below. The most important work for our study are estimates of the H-1B entry rates and population stocks, neither of which is definitively known. Lowell (2000) builds a demographic model for this purpose, and Figure 4 shows his updated estimates provided to us for this paper. The H-1B population grew rapidly in the late 1990s, before leveling off after 2000. The lack of growth immediately after 2000 can be traced to weak US employment opportunities for SE during the high-tech recession.

While demand has since grown, the reduced supply of H-1B visas now restricts growth in the H-1B population. This constraint is obscured in Figure 4, where Lowell's estimated entry rates exceed the cap. This decoupling of the numerical cap and H-1B entry rates is due to the American Competitiveness in the Twenty-First Century Act of 2000. This legislation made universities, government research labs, and certain nonprofits exempt from the cap and took effect in fiscal year 2001. We consequently focus our analyses exclusively on patents from the private-sector that have been subject to the cap throughout the 1995-2006 period. We also test in robustness checks whether using Lowell's population estimates or a measure based solely on the cap materially influences our results.

[8] See Reksulak et al. (2006) and Public Law 105-777, Division C, American Competitiveness and Workforce Improvement Law, Section 416(c)(2).

Firms in particular remain subject to the cap and their growth in H-1B usage is clearly constrained. USCIS begins accepting applications on April 1st for the following fiscal year and announces when the cap is reached. It has been reached in every fiscal year since the cap was lowered. Moreover, the cap was reached in the first day of accepting applications for the last two fiscal years. Further evidence on the high level of labor demand in SE in recent years comes from Kannankutty (2008), who documents a 2.5% SE unemployment rate in 2006, the lowest unemployment rate measured for SE since the early 1990s. While H-1B visas were historically issued on a first-come, first-served basis, a lottery has been recently employed due to rapid over-subscription. There are few additional guidelines on how the visas are allocated across applicants. This lottery system has been criticized because it does not allow for a preference ordering of candidates nor account for where high-skilled labor needs are the most pressing.

Whether the H-1B visa promotes job creation for natives is also strongly debated. In 2008 Congressional testimony, Bill Gates reported that Microsoft hires on average four additional employees to support each H-1B worker hired. A NFAP 2008 study similarly found that technology companies in the S&P 500 increased their overall employment by five workers for every H-1B visa requested. Miano (2008) and others strongly debate these claims, however, and argue that crowding-out effects occur. Our study considers employment effects for native inventors and SE workers. It is beyond this paper's scope to consider job creation or displacement for other occupations like support staff, even within high-tech firms.

As a final note, it is worth mentioning that an important shift in the type of workers using H-1B visas occurred during the 1995-2006 sample period (e.g., Hira 2004). The share of H-1B visas granted to healthcare and therapy occupations declined dramatically from 54% in 1995 to 14% in 1998. SE and computer specialist occupations grew from 25% to 57% during this same period, and the SE sector has been dominant since this inversion. We do not explicitly consider these changes due to the clear endogeneity of occupational demand — it is better conceptually to consider aggregate visa allocations and populations. It should be noted, however, that Figure 4's H-1B population estimates understate growth for SE specifically in the late 1990s.

3.2 How Much Can the H-1B Program Impact US Invention?

Our work builds on these H-1B population estimates to consider the economic consequences of changes in the H-1B program for US innovation. Given the substantial controversy surrounding the program, it is useful to frame our empirical analysis with back-of-the-envelope estimates of how large impacts from shifts in H-1B admissions can be for the US SE workforce. We estimate from the CPS a mean US SE workforce of 3.2m for 1995-2006. This includes all workers aged 20-65 with a bachelors education or above. We include computer scientists but exclude technicians from this calculation. Immigrant SE workers who are not US citizens account for 11% of these 3.2m workers, with naturalized immigrants accounting for an additional 9%.

We consider tracing the possible SE workforce consequences following a one-year increase in H-1B admissions of 65k visas. Shifts of this magnitude are well within past program changes and recent policy proposals, some of which recommend increases of more than 100k visas. Holding everything else constant, an inflow of 65k additional H-1B holders would increase the non-citizen immigrant SE workforce by 40k. This assumes that 60% of the additional visas are devoted to SE occupations, the approximate share since the late 1990s.

An additional inflow of 40k SE workers would increase the US non-citizen SE labor force by around 12% during the sample. This increase would be a 150% increase in the median annual growth rate of non-citizen SE workers. It would be even larger for Indian and Chinese SE populations, given their concentrated role in the H-1B program. Unfortunately, the CPS does not distinguish H-1B holders from other temporary worker categories[9] or non-citizen permanent residents. H-1B workers account for the large majority of temporary SE workers, however, and the estimated net growth in H-1B SE workers can fully explain the net growth of non-citizen immigrant SEs during 1995-2006.

Overall, the 40k worker inflow would increase the total US SE labor force by about 1.2%, holding everything else constant. This increase would be about half of the median annual growth rate of SE workers, calculated at 2.7% during the period. The total SE workforce would grow by less, or even contract, if new arrivals crowd-out domestic counterparts. On the other hand, overall growth could be larger if immigrants crowd-in domestic activity. Regardless of crowding-in or crowding-out effects, however, our calculations show that the H-1B program does not have sufficient size to dramatically alter aggregate levels of US invention in the short run that our work studies. Said simply, doubling the H-1B cap will not double the total number of new US patents over the next five years. On the other hand, the program does have the size to substantially influence the growth rate of US invention, which is what our empirical specifications test. Faster innovation growth would have substantial economic impacts when compounded over time. Moreover, concentrated impacts would exist for very dependent cities and firms.[10]

[9] For example, the L-1, TN, exchange visitors (J), or immigrants of extraordinary ability (O) visas

[10] These estimates are order-of-magnitude only. The CPS was redesigned in 2003 to conform to the 2000 Census. This redesign unfortunately produces substantial coding breaks for many variables of interest to this study. As noted below, US patenting in recent years extends beyond traditional SE fields to areas like financial services. These SE calculations abstract from these other sectors.

3.3 Available H-1B Data

The above calculations can bound the potential impacts of the H-1B program but they do not establish that a link exists between H-1B visa levels and US innovation patterns. To characterize this linkage, we assemble the available data specific to the H-1B program. The American Competitiveness and Workforce Improvement Act of 1998 requires that information about successful H-1B visa applications be submitted each year to Congress. Our first data source are these "Characteristics of Specialty Occupation Workers (H-1B)" publications, which provide the broad statistics cited in this paper.

Our second data source comprises two lists of the top US firms that sponsor H-1B visas. The first list was published by the US Immigration and Naturalization Services and documents the top 102 employers that received H-1B visa approvals over a five-month period starting in October of 1999 (1999 Top 100). The second list was published by *BusinessWeek* magazine and contains similar information for the top 200 H-1B employers in the 2006 fiscal year (2006 Top 200). Both of these lists are flow measures of within-period H-1B approvals, rather than stock measures of total visa reliance. These two lists, along with an update *BusinessWeek* made in 2007, are the only data we have been able to assemble on firm usage of these visas.

Our third data source consists of published micro-records on Labor Condition Applications (LCAs). To obtain an H-1B visa, an employer must first file an LCA with the US Department of Labor (DOL). The primary purpose of the LCA is to demonstrate that the worker in question will be employed in accordance with US law. The second step in the application process after the LCA is approved is to file a petition with the USCIS, which makes the ultimate determination about the visa application. The DOL releases micro-records on all applications it receives, numbering 1.8m for the 2001-2006 period. These records include (1) the name of the firm, (2) the proposed work location (city and state) and wage, (3) a categorization of the type of job, and (4) relevant dates. The appendix provides a complete description of this resource and its preparation. These data are a foothold for examining both city and firm dependencies, although it should be noted that LCA approvals do not translate one-for-one into H-1B grants.

3.4 Indian Firms and H-1B Visa Usage

Before examining the relationship between innovation and H-1B visa levels, it is worth discussing the use of these visas by Indian firms. In the 2006 Top 200 list, four of the top five users of H-1B visas were Indian firms like Infosys and Wipro. This represented a substantial increase in the ranking of Indian firms from the 1999 Top 100 list, which was mostly dominated by American firms. Many detractors of the H-1B program point to this concentration among foreign firms as evidence that the H-1B program is now serving as a vehicle for staffing by foreign firms, with possible off-shoring motivations, versus addressing the SE needs of US firms.

Our analysis does not address this aspect of the H-1B program. These Indian firms have only a handful of patents in the US, so our city-level measures of US innovation rates by Indian inventors are not materially influenced. We also restrict our firm panel to publicly listed US companies. If anything, shifts in the last few sample years towards greater visa usage by Indian firms reduce estimates of the impact that visa levels have for US innovation outcomes. We hope to explore the use of H-1B visas by Indian firms in future research.

4 City-Level Analysis of the H-1B Program

We now turn to reduced-form estimations that quantify whether shifts in H-1B admission levels are correlated with stronger or weaker innovation in dependent cities. The next section extends this framework for firm-level analyses.

4.1 Empirical Strategy and Data Set Development

We begin by outlining our estimating equation and then work backwards to relevant variables and parameters. Our estimations quantify the H-1B program's effects by examining relative impacts across cities. We group cities into five quintiles of dependency, with each quintile containing 56 or 57 cities. These city groupings are fixed, and we discuss below how dependency levels are specifically measured.

Our baseline specifications take the form,

$$\begin{aligned}\ln(PAT^{Dep}_{c,t}) \;=\;& \phi_c + \eta_t \\ & + \beta_1 \cdot [I_c(\text{Top Quintile}) \cdot \ln(\text{H-1B}_t)] \\ & + \beta_2 \cdot [I_c(\text{2nd Quintile}) \cdot \ln(\text{H-1B}_t)] \\ & + \beta_3 \cdot [I_c(\text{3rd Quintile}) \cdot \ln(\text{H-1B}_t)] + \epsilon_{c,t},\end{aligned} \tag{2}$$

where ϕ_c and η_t are vectors of city and year fixed effects, respectively. Our dependent variables of interest are the log of the number of ethnic and overall patents by city. H-1B$_t$ is a measure of the visa-holding population in year t. We lag the years shown in Figure 4 by one year to align USCIS fiscal years with calendar years for patents. Before interacting, logarithms of H-1B$_t$ are taken to remove scale dependency.

$I(\cdot)$ are three indicator variables for whether city c is in the 3rd, 2nd, or most dependent quintiles of H-1B dependency. The bottom two quintiles, accounting for 40% of US cities but only 1% of LCA applications, serve as the reference group. Effects for the top three quintiles are measured relative to this group. This flexible specification thus tests whether innovation patterns in cities thought to be dependent upon H-1B workers are more or less sensitive to changes in H-1B population levels. Considering the top three quintiles separately allows us to test for non-linear effects in the city distribution. Main effects for $I(\cdot)$ and $\ln(\text{H-1B}_t)$ are absorbed into the panel fixed effects ϕ_c and η_t. Only the residual variation is exploited for identification.

This approach, absent omitted variable biases, properly identifies treatment effects if H-1B admission decisions are made nationally by the US federal government but have heterogeneous impacts across cities due to local differences. This reduced-form approach also circumvents concerns surrounding endogenous sorting across markets by workers. On the other hand, estimations for the top quintile can be biased upwards if a small group of cities or firms exerts a substantial impact on admissions decisions, through lobbying and similar efforts, and likewise receives disproportionate impacts. The non-parametric nature of (2) addresses this problem by directly examining impacts on invention in the second and third quintiles that have very little or no influence on H-1B admission choices. We will also test the robustness of the treatment effects in the top quintile by dropping cities with extreme sensitivity to the program.

Defining cities as the relevant market for these effects is an important decision. The appropriate market definition should reflect the speeds of SE labor, product, and technology flows. One perspective is that the SE market is national in scope. This is certainly true in the long run given the high mobility of skilled workers and the H-1B program's national quotas. In this case, limited progress can be made with geographic variation. On the other hand, many industry executives suggest they operate in a very constrained environment, and the H-1B visa is specific to a firm-worker match. In this case, one could argue that the short-run analysis is best undertaken at the level of the firm or perhaps across a grouping of very dependent firms.

We believe that cities are an appropriate choice, however, given the location-specific nature of H-1B visas, local labor mobility, and short-run rigidities in firm location choices. Agglomeration studies typically identify cities and commuting regions as the relevant spatial unit for labor market effects on firms, and technology spillovers are found to operate at even shorter distances (e.g., Rosenthal and Strange 2001, 2003, Ellison et al. 2007, and Glaeser and Kerr 2008). Cities are also more appropriate than states as economic units in this context. For example, a state-level dependency for North Carolina would mask substantial differences between Raleigh-Durham and Wilmington, among the most and least H-1B dependent cities nationally. From an econometric perspective, this granularity allows for stronger regional trends and controls. In the next section, we will also examine firm and sector level variation to test the arguments put forth by high-tech executives.[11]

Our first measure of a city's dependency on the H-1B program is derived from the microdata on LCAs collected by the DOL. This measure is constructed as the yearly average of the city's LCAs in 2001-2002 normalized by the city population. There are several advantages of this metric. First, it is very closely tied to the H-1B program and can be measured for all cities. Second, the metric can be extended to the firm level, a disaggregation that we exploit in Section 5. Finally, LCAs measure latent demand for H-1B visas — demand is measured independent of whether an H-1B visa is ultimately realized or not. Moreover, the demand is real in that non-trivial application and legal costs exist, and firms must list individual candidates on accompanying documents. These strengths of the LCA-based dependency make it our preferred metric, although its measurement during the sample period may upwardly bias measured treatment effects.

Given this latter weakness of the LCA metric, our second measure is the 1990 count of immigrant SEs in the city who are not US citizens, again normalized by city population. It is calculated from the 1990 Census of Populations. This metric is much more conservative, being entirely measured before the 1990s growth in SE immigration evident in Figures 1-3. This measure also has the nice advantage of allowing contrasts with Canadian cities that we exploit below. Its primary disadvantage is that the non-citizen immigrant category includes permanent residents and many types of temporary workers besides H-1B holders (e.g., exchange visitors, students). Measurement error in the regressor of this form will bias elasticity estimates downward from their true treatment effects.[12]

Table 3 documents the twenty most dependent cities for each metric. A number of big cities are dependent upon the H-1B program, which is similar to other immigration clustering, but many smaller cities are influenced as well. San Francisco is the most dependent city in the LCA-based ranking. In the Census-based ranking, Lafayette - West Lafayette, IN, and Bryan-College Station, TX, are ranked higher than San Francisco. These cities are home to Purdue University and Texas A&M University, respectively, and their surrounding SE industries. Other heavily dependent cities include Raleigh-Durham, Boston, and Washington, although considerable variation exists outside of the top rankings. The least dependent cities are Pascagoula, MS, and Rapid City, SD, according to the LCA and Census metrics, respectively. The pairwise correlation of the two rankings is 0.5 across all cities. While we report the raw dependencies

[11]Borjas (2003) argues analyzing immigration through education-experience cells under the assumption of an otherwise national labor market. The H-1B program is almost entirely confined to workers with bachelors education levels and above, limiting the effectiveness of this technique.

[12]We employ the IPUMS 5% state sample for these calculations to maximize sample size. This prohibits us from calculating direct metrics for small cities that comprise about 20% of the sample. For these cases, we employ the state-level dependency. We find similar results if we drop these cases.

in Table 3, we only use these numerical values to order cities for the quintile groupings. The appendix describes these data sources and preparation in greater detail and further documents the dependencies of major patenting cities.

4.2 City-Level Empirical Results

Tables 4A and 4B present our baseline empirical results using city-level variation. Column headers indicate dependent variables. We test for effects on the log level of city patenting for four ethnic groups: Indian, Chinese, other non-English ethnicities, and English inventors. The Other Ethnicity category excludes Indian, Chinese, and English inventors. The fifth column considers total patenting in the city. We cluster standard errors by city.

The first column of Panel A in Table 4A finds a positive relationship between increases in H-1B visa allocations and Indian patenting in dependent cities. The upper left coefficient of 0.313 suggests that a 10% increase in the H-1B population is associated with a 3% increase in Indian patenting for the middle quintile relative to the bottom 40% of cities. Effects are larger for the upper two quintiles, suggesting 6% and 10% increases in patenting relative to the reference group. These β estimates are statistically precise and economically meaningful in size relative to Indian patenting. Moreover, the 10% increase discussed is realistic as the average annual increase in the H-1B population during the sample period is 8%. These simple empirics thus support our hypothesis that the H-1B visa program has a substantial impact on the level and spatial location of Indian patenting.

Column 2 finds a slightly larger correlation between Chinese invention and the city dependency interaction. While we anticipated that Chinese inventors would show an important dependency on the H-1B program, the comparable elasticity to Indian invention is somewhat surprising given that the Chinese H-1B inflow is smaller relative to the overall population of Chinese inventors in the US. Several factors likely lead to more equal elasticities, including a weaker propensity among marginal Indian H-1B holders to engage in patenting compared to Chinese holders. This also might reflect crowding-in effects for other Chinese inventors, which we will see some suggestive evidence of below. While city-level exercises find comparable Indian and Chinese effects, the Indian response is found to be stronger in the firm panel considered in Section 5.

The more significant contrasts are between Indian and Chinese inventors in Columns 1 and 2 and other ethnicities in Columns 3 and 4. Column 3 shows that other non-English ethnic groups (e.g., European, Hispanic, Korean) increase patenting in dependent cities, too. This response is substantially smaller in magnitude than Indian and Chinese estimates in the upper two quintiles, however, and the linear differences are statistically significant. This confirms our expectations about the distribution of impacts of the program across different immigrant groups.

Column 4 further finds that English invention in dependent cities is weakly correlated with shifts in H-1B admissions. Although none of the estimates is statistically significant, we estimate that a 10% increase in the H-1B population is associated with a 0.5%-1% increase in English invention in the top two quintiles relative to the reference group. These elasticities are about a tenth of the relative magnitudes estimated for Indian and Chinese inventors. Note that this is a matter of relative economic importance rather than statistical precision, as standard errors are roughly uniform across columns. While not significantly different from zero, the positive response of English invention provides some evidence against immigrants associated with the H-1B program crowding-out US natives in large numbers. A strong interpretation would further suggest a modest crowding-in effect.

The final column finds a positive effect for total patenting. The weaker effect for total invention compared to Columns 1 and 2 is to be expected given that Indian and Chinese inventors comprise about 13% of all US domestic patenting during the period studied. The estimates suggest that a 10% growth in the H-1B worker population is associated with a 2% increase in patenting for the most dependent quintile relative to the bottom 40% of cities. Effects are smaller at 0.4%-0.8% for the second and third quintiles.

Panel B of Table 4 repeats the estimations with the Census-based dependency. The overall picture remains the same as in Panel A, especially the ordering across ethnicities. Elasticities with the Census-based dependency are smaller across the board, likely due to a combination of greater conservatism and more measurement error in the estimated dependencies. The positive association with growth in English invention is no longer present in the top quintile but it does persist in the second and third quintiles, albeit insignificantly. The results for the growth in total invention are much weaker, a pattern more suggestive of the H-1B program not having any effect on native inventors.

Thus, the results in Table 4A mostly conform to Section 3's expectations. The H-1B program has a substantial impact on the location of Indian and Chinese invention, and it appears to be associated with a small increase in English invention rates as well. However, it is natural to worry whether the reduced-form interaction in (2) is capturing other heterogeneity across cities than H-1B dependency or other time effects than the aggregate shifts in H-1B admissions. The ordering of effects across ethnicities provides helpful assurance in the story presented. Other explanations would need to similarly explain localized impacts among Indian and Chinese inventors.

One plausible, alternative explanation is that differential growth in patenting rates across technology sectors produce Table 4A's ethnic differences. Table 1 noted that Indian and Chinese inventors are more concentrated in high-tech sectors than other ethnic groups. Some of these sectors over the last two decades, such as software development, increased their propensity to seek patent protection for a given rate of innovation. To the extent that these institutional shifts and other sector-specific changes overlay the H-1B aggregate trends modeled in equation (2), the estimated β parameters will be biased upward. Relative differences in ethnic concentration across technologies in Table 1, however, suggest that this factor is unlikely to account for the full effect measured in Table 4A.

Table 4B accounts explicitly for these technology trends by including measures of the expected city-level patenting for each ethnic group. We construct these metrics by first calculating the mean annual patenting done in the focal city by each ethnic group over 1990-1995 in 36 technology sectors. These sectors are the sub-categories of patent classifications; examples include "Resins", "Computer Peripherals", and "Optics." We then take subsequent growth in national patenting for each sector, weight these trends by the city's pre-period composition, and sum across technologies. To maintain a consistent specification and to maximize explanatory power, we include the expected patenting trends for all four ethnic groups in each estimation.

These trends control for national patenting growth by sector in a manner specific to a city and ethnicity. They account for potential shifts in patent propensity, as well as other sector-specific issues like industry cycles. It is important to understand, however, that controlling for technology trends is a substantive restriction in the H-1B context. Many high-tech industry executives argue that their whole sector is hurt by the reduced H-1B admissions, and differentially so from less dependent industries. Under this scenario, technology trends remove first-order effects of H-1B policies that our estimations should capture.

Coefficients for these ethnic-specific technology trends are documented in Panel A of Table 4B. Each ethnicity is particularly dependent on the expected trend for its own ethnicity. One exception is that Chinese inventors experience rapid increases in cities with strong expected Indian patenting growth. This effect mostly descends from early Indian concentration in information technology and computer-related clusters. This pattern is consistent with a crowding-in effect for existing US Chinese surrounding the H-1B program that was noted above when discussing the equal Indian and Chinese elasticities. We find very similar results for the coefficients on these ethnic-specific technology trends when using the Census-based dependency.

When we introduce these trends, the relative ordering of effects remains the same as in Table 4A. Indian and Chinese elasticities do decline, however, while measured elasticities for English and total invention increase. The English inventor elasticity is a fourth of the Indian and Chinese elasticities in the LCA-based regressions, and the total patenting response is consistently different from zero. These LCA-based results suggest a stronger crowding-in effect for English invention than estimations that did not control for technology rates. The Census-based results, however, continue to find little evidence for crowding-in or crowding-out effects.

To summarize, shifts in the H-1B program are found to increase Indian and Chinese invention in dependent cities across all estimations. We typically find small, positive elasticities for English invention, with most estimates not statistically different from zero. Elasticities for total invention are slightly larger and more frequently statistically different from zero. Combining the median of these elasticity estimates with the relative sizes of inventor groups, we estimate that 20%-40% of the total patenting gains associated with increases in H-1B visas accrue through English inventors. This would imply that indirect contributions are approximately half of the direct contributions on immigrant SEs. This is weaker than the three-quarters effect evident in the simple correlations of Section 2. These effects tend to be smaller in the most dependent quintiles and larger when controlling for technology trends.

Partial R^2 values measure the explanatory power of the regressors after we remove panel fixed effects and technology trends. We generally find that 4%-5% of the Indian and Chinese variation at the city level can be explained by the dependency interaction. This explanatory power is higher at 15% if technology trends are included. The explanatory power for English invention is 0.5% and just over 1% for total innovation. Overall R^2 values typically exceed 90%.

4.3 City-Level Robustness Analysis

The appendix documents several important robustness checks on these findings. We first substitute the six-year summation of the annual H-1B visa cap in place of Lowell's H-1B population estimates for H-1B$_t$ in equation (2). We model six-year summations instead of three-year summations as renewals of H-1B visas do not apply towards subsequent caps. The cap summation introduces more measurement error into the H-1B population estimate but it perhaps benefits from stronger exogeneity. The results are very similar with this alternative estimation, since the cap has been binding in most years. Generally, the choice of H-1B$_t$ is of second-order importance to the dependency measure employed.

We also find similar results with several variants to the specification in equation (2). Robust results are found when incorporating state-year fixed effects or dropping the West Coast of the US. This stability argues against omitted variable biases at the regional level driving the observed outcomes. The results are also not the exclusive product of the high-tech sector's growth in California, Oregon, and Washington. We further find similar results when testing before and after 2001, when separately employing granted patents only, and when using a first-differenced specification. The findings also hold when controlling for quintiles of city population or when controlling for growth in US citizen immigrant SEs through additional interaction terms in equation (2).

We finally undertake tests confirming the extent to which effects are evident throughout the city dependency distribution. These tests are important as political economy factors influence nationally-set visa levels (e.g., Reksulak et al. 2006, Facchini et al. 2008). Year effects account for these aggregate levels but these controls are insufficient if a handful of cities or firms exert extensive lobbying and receive disproportionate impacts.

Our quintile-based specifications already provide comfort against this reverse causality story. Sensitivity to H-1B admission fluctuations grows monotonically with dependency. But while the strongest associations are evident in the most dependent grouping, consistent and measurable effects were also evident in the second most dependent quintile. San Francisco, Austin, and similar cities may influence admission levels through lobbying efforts but the second quintile accounts for only 9% of LCA applications versus 86% for the upper quintile. This concentration is due to both smaller dependency levels and smaller absolute city size on average. Finding effects in this second quintile is reassuring.

The appendix further documents estimations that drop all patents associated with 307 of the most highly-dependent firms that we could identify. These firms account for 30% of patents during 1995-2006 and are discussed in more detail in Section 5. This grouping includes the most frequent LCA applicants and the largest US patentors. Our results are robust to this technique, confirming that the important effects estimated for the second quintile are not due to a few influential firms patenting in several cities. We also find similar coefficients for the top quintile when dropping the 20 most dependent cities of this group. These 20 cities account for 70% of all LCAs in the most dependent quintile, suggesting again that the results extend deeper than the extreme cases like San Francisco and Boston.

4.4 Lag Structure of Treatment Effects

Table 5 presents a lag structure analysis using a dynamic version of equation (2). The dependent variable is the log growth in ethnic patenting from year $t-1$ to year t. We consider forward, contemporaneous, and lagged changes in the H-1B population over two-year intervals. These dynamics are interacted with the three quintile groupings. Our contemporaneous specifications in Tables 4A and 4B are motivated by empirical studies finding that contemporaneous R&D investments have the most important impact for rates of technology formation. In the context of this paper, we consider how recent investments in hiring high-skilled immigrants affect innovation. The dynamic specifications test whether this contemporaneous empirical strategy is reasonable or not.

The patterns in Table 5 are reassuring. Contemporaneous effects are the strongest in all three quintiles relative to the reference group. As importantly, limited effects are evident on forward changes or long-term lags. Two exceptions are important to note. First, lead values exist for Indian and Chinese invention in the most dependent cities. While these estimates are not statistically different from zero, their size provides some prima facie evidence that the admissions levels of the H-1B program may respond to strong visa demand. On the other hand, it is very reassuring that lead effects are not evident for the second quintile, which demonstrates a responsiveness to changes in H-1B admissions levels.

A second point of interest is the pattern of English invention over time. Contemporaneous gains are evident, but both forward and long-term values are negative, albeit insignificantly. Summing across the changes indicates that English invention does increase, but the aggregate effects are smaller than the contemporaneous gains indicate. This is in contrast to the other ethnic groups and total invention where strong, positive gains exist when summing across the whole lag structure. These pattern suggests that crowding-in effects estimated through the contemporaneous specification may be transitory. These patterns are more consistent with invention gains primarily accruing through the new immigrants themselves.[13]

4.5 Comparison to Canadian Cities

Canadian cities provide a useful baseline for comparing the estimated effects of the H-1B program on US ethnic invention patterns. Indian and Chinese inventors account for about 15% of Canada's patents during the 1995-2006 period, only slightly more than in the US, and the technology breakdowns are similar for the two countries. We therefore test whether Canadian cities display similar or different trends to those found in the US.

Identical trends in Canada and America would warn that our dependency metrics are biased by other secular changes. As US and Canadian high-skilled immigration generally followed similar trends during this period, an example would be Indian and Chinese immigration to North America interacting with past immigrant networks. However, we cannot state in advance that a null result for Canadian cities is the expected outcome either. Greater immigration to the US through the H-1B program may encourage parallel immigration to Canada. Higher H-1B admission levels could alternatively reduce Canadian SE immigration if the number of visa seekers from India and China to North America is constant.

[13] While the H-1B population lag structure is consistent with a contemporaneous specification, lag structures that employ six-year cap summations are not well defined across the full 1995-2006 period. Forward or lagged effects can be present, and the estimations are much more sensitive to specification design than those that model H-1B population estimates for H-1B$_t$. This weakness is anticipated in Figure 4, as the strongest surge in the six-year cap summation is during the early 2000s recession, when visa demand fell short of the available cap. On the other hand, lag structures for cap summations are consistent during periods when the cap is constraining.

The data extension is straightforward and described in detail in the appendix. Many Canadian inventors seek patent protection from the USPTO. Using approximately 150k granted patents and 65k non-overlapping applications filed from Canada, we estimate the ethnic composition of Canadian inventors in 49 metropolitan areas that are comparable in size and scope to the US Metropolitan Statistical Areas through which we define US cities. Likewise, the 1990 Canadian Census of Populations (IPUMS) is used to construct non-citizen immigrant SE dependency metrics roughly similar to our Census-based metrics for the US. We are able to construct city-level dependencies for 22 cities and province-level dependencies for 27 cities. The most dependent major Canadian cities are Toronto and Vancouver.

The Canadian sample is unfortunately too small for a quintile analysis. Instead, we group cities into whether they are above or below the median dependency of their country in a simple variant of equation (2). Panel A of Table 6 first re-estimates the US sample with this empirical approach. The outcomes are very similar to the bottom of Table 4A. Panel B then estimates the same relationship after we drop the most dependent quintile of the US distribution. We undertake this second step as the most dependent Canadian cities, to the extent that we can align the different data sources, fall in the second highest quintile of the US dependency distribution. This also removes the most worrisome US cities in terms of political economy factors. English and total patenting outcomes are somewhat stronger in this restricted sample.

Panel C undertakes a similar analysis with the full Canadian sample, while Panel D drops cities for which we cannot directly calculate dependencies. None of the results across the different specifications show estimates that are significantly different than zero. These Canadian differentials hold across other specification variants, such as including ethnic technology trends and using the six-year cap summation. These results are again reassuring for our empirical design. Although some of the point estimates might provide suggestive evidence that fluctuations in the H-1B visa quota have impacted Canadian innovation — perhaps even to reduce Indian invention when admission rates to the US are high — we mainly consider these estimates as a confirmation that our results are not being driven by other secular factors unrelated to H-1B admissions.

4.6 State-Year Estimations from the CPS

As a final check on our city-level results, we employ state-year variation in SE populations measured in the CPS. Since 1994, the CPS identifies whether respondents are non-citizen immigrants, citizen immigrants, or US natives. While this direct observation of immigration status is an important complement to our ethnic inventor records, the CPS brings substantial liabilities. Most importantly, the CPS is designed as a representative sample for the US, not for small geographic areas like cities and states. As a consequence, we only observe immigrant SE workers consistently over 1995-2006 in 26 states. Even for these complete series, small sample sizes also result in substantial measurement error. Second, the CPS redesign in 2003 creates a structural break in variable definitions between 2002 and 2003. As a consequence, we employ exclusively first-differenced specifications that drop 2002-2003 changes. This dropped year is an important inflection point for the H-1B program but there is no way to separate economic changes from coding changes through this survey.

Despite these caveats, the CPS yields comparable results to our ethnic patenting findings. Panels A and B of Table 7 first look at simple correlations between immigrant SE growth and domestic SE growth. These correlations are restricted to the sample of 26 states for which immigrant SEs are continually observed, for a total of 260 observations. Panel A finds that growth in non-citizen SE immigrants is weakly correlated with native SE growth by state. Panel B finds stronger coefficients when using total immigrant SE growth as the regressor. Panel B's coefficients suggest that a 10% growth in immigrant SEs is correlated with a 0.5% and 1.6% growth in native and total inventor populations, respectively. As in Section 2, the interpretation of these correlations is limited but they do provide some support for the exercises in Table 2.

Panels C and D document reduced-form specifications with the LCA and Census dependencies similar to those found in equation (2). Due to the limited sample size, we only contrast states above the median dependency level with those below the median. Columns 1-4 restrict the panel to the 26 states for which some measure of immigrant SEs is observed in each year. Columns 5 and 6 test native and total patenting responses across all states. These reduced-form interactions are very similar to the ethnic patenting responses. Column 1 finds growth in non-citizen SEs with higher H-1B admission rates. Column 2 finds a weaker elasticity for total immigrant SE workers, which is to be expected. These results confirm the importance of the H-1B program for explaining the spatial locations and growth of immigrant SEs through a second data source.

Column 3 finds mixed evidence regarding crowding-in or crowding-out effects for native SE workers. The LCA-based interaction suggests a positive response, while the Census-based dependency is negative. Column 5 suggests that these differences are likely due to the restricted state sample. When considering all states — and native SE workers are observed in all state-years — both dependencies yield positive growth effects for native SEs. The total SE workforce is consistently found to increase in dependent states relative to non-dependent states when H-1B admissions are higher. The CPS thus documents qualitatively similar trends to our primary specifications.

5 Firm-Level Analysis

We extend our city-level results with a firm-level analysis that exploits additional detail that is possible with the ethnic patenting data set. Many high-tech industry executives argue that their firms are especially prone to fluctuations in H-1B admissions. We create a panel of the most H-1B dependent firms to test this claim. Figure 5 describes the share of total Indian and Chinese invention in five of these major firms over time. Substantial heterogeneity exists across firms in levels of ethnic invention and trends. This level of detail allows us to characterize impacts of H-1B visa changes in an alternative way to our city-level analysis. It is the first large scale description of ethnic invention within firms and the first analysis of the link between immigration and innovation at the firm level of which we are aware.

5.1 Ethnic Inventor Compositions Within Firms

We restrict our sample to very dependent firms and their close peers. We define our initial sample according to the following criteria: (1) firms included in the 1999 Top 100 and 2006 Top 200 lists of H-1B sponsors; (2) firms with assignee names accounting for 0.05% or more of patent grants or applications during 2001-2004; and (3) firms with assignee names accounting for 0.03% or more of LCA applications during 2001-2006. Of the 592 unique firms that satisfy one or more of these criteria, 307 have at least one patent during 1995-2006. These firms account for more than 500k granted patents and unique applications to domestic inventors over 1995-2006; they represent about 30% of all US patents with domestic inventors during this period.[14]

Of this sample, 177 firms are publicly listed and have at least one US domestic patent in every year from 1995 to 2006. Tables 8 and 9 detail general characteristics of these firms. They have over 130 patents on average per year, with a standard deviation of almost twice that amount. The ethnicity and geography of inventors in these firms broadly match US aggregates. One notable exception is that sampled firms tend to patent more in Computers and Communications technologies, which is to be expected from our focus on firms likely dependent on H-1B visas. A comparison of means and medians across these different technology categories and regions also demonstrates that firms tend to specialize in particular types of innovation and to spatially cluster their innovations. Sampled firms are generally quite large, although substantial variance exists in sales, employees, and R&D expenditures. More generally, the median-to-mean gap in

[14] Creating this panel was the most intensive part of this project. The appendix lists included firms, details our selection methodology, and provides descriptive statistics. We also describe the extensive work undertaken to account for multiple assignee names per firm and major corporate restructurings. The developed sample is not sensitive to looking at top patenting firms in different periods (e.g. top patentors during 1995-2006 versus 2001-2004).

many metrics (e.g., sales, LCAs, annual patents) shows that the distribution of firm size in the sample is left skewed.

Table 9 analyzes these firm characteristics in a multivariate setting. We estimate these regressions at the firm level, aggregating over all of the years in our sample. In each year we first construct the share of the firm's total patents in each technology category and similarly construct the share of the firm's patents in each region. We then regress the total number of patents for each ethnicity on these technology and geographical specialization variables as well as on measures of firm size. Column headers in Table 9 indicate ethnic inventor shares considered, and each row's coefficients sum to zero. Several results stand out. Larger firms and those that are more specialized in high-tech innovations tend to have higher shares of Indian and Chinese inventors. Geography also matters. Firms undertaking most of their innovative activity in the New England, Middle Atlantic, or West Coast regions have higher average shares of ethnic inventors. Overall, R^2 values range from 0.35 to 0.53, indicating a substantial degree of explanatory power. Technology and geographic concentration accounts for more of this explanatory power than firm size.

5.2 Empirical Results

To evaluate the temporal impact of H-1B policies, we restrict our sample to 76 firms. All of these firms are publicly listed, based in the US, have at least five patents per year, and have at least one inventor of each relevant ethnicity in every year from 1995 to 2006. The publicly-listed restriction allows us to utilize Compustat employment and sales data from 1990-1995 for normalizing our dependency metric. The ethnic patenting restriction focuses attention on the intensive margin for this analysis.

The firm specification takes the form,

$$\begin{aligned} \ln(PAT^{Dep}_{f,t}) \;=\; & \phi_f + \eta_t + \gamma \ln(ExpPAT_{f,t}) \\ & +\beta_1 \cdot [I_f(\text{More Dependent, Computer}) \cdot \ln(\text{H-1B}_t)] \\ & +\beta_2 \cdot [I_f(\text{Less Dependent, Computer}) \cdot \ln(\text{H-1B}_t)] \\ & +\beta_3 \cdot [I_f(\text{More Dependent, non-Computer}) \cdot \ln(\text{H-1B}_t)] + \epsilon_{f,t}, \end{aligned} \tag{3}$$

where ϕ_f and η_t are vectors of firm and year fixed effects, respectively. We group firms into four categories based upon two dimensions: (1) degree of dependency on the H-1B program, and (2) whether the firm's innovations are oriented towards the computer sector or not. We measure the first dimension of H-1B dependency through each firm's 2001-2002 LCA filings normalized by Compustat sales. We identify the second dimension through a firm's most frequent patent category. As in Table 1, the six main patent categories are Chemicals, Computers, Drugs, Electrical, Mechanical, and Miscellaneous. Firms with most of their patents in the second category are deemed computer-oriented for this analysis.

We then interact H-1B_t with indicator variables for more dependent computer firms, less dependent computer firms, and more dependent non-computer firms. Effects for these firms types are measured relative to less dependent firms outside of the computer sector. Main effects for interactions are again absorbed into panel effects. We include a firm-specific measure of expected patenting $ExpPAT_{f,t}$ to control for different technology trends over time. Unlike before, however, we do not construct ethnic-specific technology trends given the limited pre-period data for many firms.

Table 10 presents the firm-level findings. Ethnic invention, and Indian invention in particular, is closely tied to H-1B admissions levels in more dependent firms in the computer sector. A 10% growth in H-1B admissions correlates with an 8% growth in Indian invention relative to the reference category of less dependent firms outside of the computer sector. Point estimates for highly dependent firms outside of the computer sector are similar to less dependent firms in the computer sector, suggesting a 2% differential for both. It should be noted that the firm panel was constructed around firms expected to be dependent upon the H-1B program, so the baseline category is not weakly dependent as in the city-level analysis. Instead, the results point to particularly powerful and disproportionate impacts even among heavily influenced firms.

The fourth column documents the level of English invention. Unlike ethnic invention in Columns 1-3, higher H-1B admissions are not associated with exceptional growth in English patenting in more dependent firms in the computer sector. In fact, the growth is slightly weaker than that experienced by more dependent firms outside of the computer sector. The results suggest that additional patenting gains in more dependent high-tech firms primarily accrue through immigrants themselves. Crowding-in or crowding-out effects for natives do not appear to be strong in these special cases.

This firm-level analysis is a nice robustness check on the city-level approach. It substantiates claims of high-tech executives that their firms are especially vulnerable to high-skilled immigration policies for temporary workers. On the other hand, the results do not point to large crowding-in or crowding-out effects. As some of these firms are among the primary lobbyists for H-1B legislation, these results should be interpreted as partial correlations only.

6 Conclusion

Over the last fifteen years, the H-1B visa program for temporary workers has played an important role in US innovation patterns. As immigrants are especially important for US innovation and technology commercialization, this makes the H-1B program a matter of significant policy importance. We find that fluctuations in H-1B admissions levels significantly influence the rate of Indian and Chinese patenting in cities and firms dependent upon the program relative to their peers. Most of our specifications also find weak crowding-in effects or no effects at all for native patenting. We conclude that total invention increases with higher admission levels primarily through the direct contributions of immigrant inventors.

We close with a discussion of four related research questions outside of the scope of this study that we hope that can be addressed in future work. First, we have focused exclusively on the H-1B program given its particular importance in SE and large admissions fluctuations. We hope that future research will consider other temporary visa categories. The H-1B program has unique characteristics that are not shared by many other immigrant categories. Quantifying employment effects due to other visa programs will clarify whether our weak crowding-in results apply generally or are due to the particular features of the H-1B program. For example, the prevailing wage requirement may limit crowding-out effects to the extent that the requirement is followed. Likewise, the manner in which H-1B workers are tied to their sponsoring firms may produce special outcomes. Such comparative assessments will also aid policy makers when crafting future immigration policies.

Second, our analysis considers high-frequency variation over twelve years. We are not able to quantify the long-run impacts of these policy choices as a consequence. Given the time and expense involved in training new SEs, long-run crowding-in and crowding-out effects for natives can differ from short-run effects. Fluctuations in the H-1B cap are quite recent, so researchers will need to unite our work with studies exploiting low-frequency variation to understand these dynamics (e.g., Hunt and Gauthier-Loiselle 2008). This characterization would in turn be an important input into future theoretical work on how the supply side of innovation influences overall US technology growth.

Third, our analysis quantifies city-level patenting growth due to higher H-1B admission rates in broad terms. There are many research groups operating within cities: firms, universities, government labs, private inventors, and others. We have not analyzed how changes in the H-1B program alter the local relationships among these different institutions. For example, the current comparative advantage of universities for obtaining H-1B visas may result in greater dependencies of local industry on universities for certain forms of SE advancement. Understanding these local inter-linkages will be informative for both H-1B program assessments and of general interest for technology transfer studies.

Finally, although ethnic patenting data allows us to characterize the role of H-1B workers for US innovation in a unique way, we recognize that the H-1B program impacts many other aspects of the US economy. Indeed, about half of the major employers of H-1B visas that we identified for our firm sample did not file for a patent during our period of study. Future research should quantify the economic impacts for other sectors like accounting and consulting firms, banks and financial institutions, and public services in ways that are appropriate for these sectors. It will likewise be particularly interesting to quantify job creation or displacement effects for occupations other than inventors among high-tech firms.

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Fig. 1: Ethnic Share of US Domestic Patents

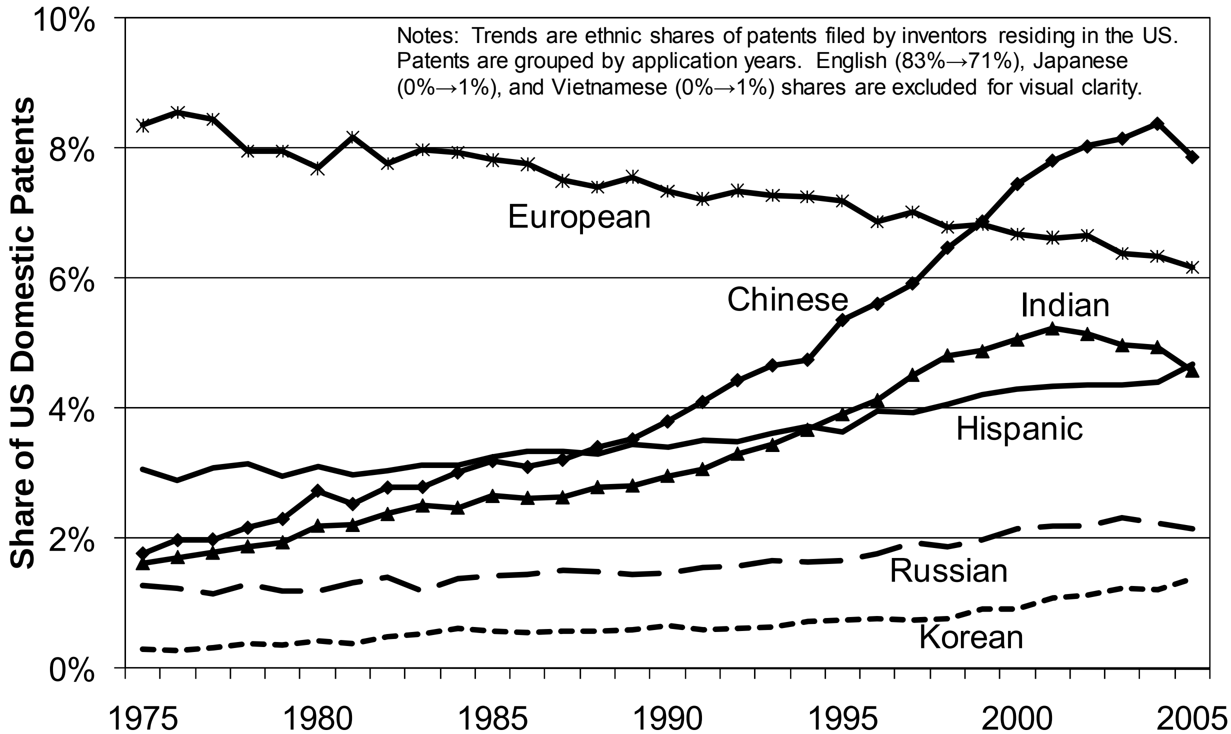

Fig. 2: Indian Contribution by Technology

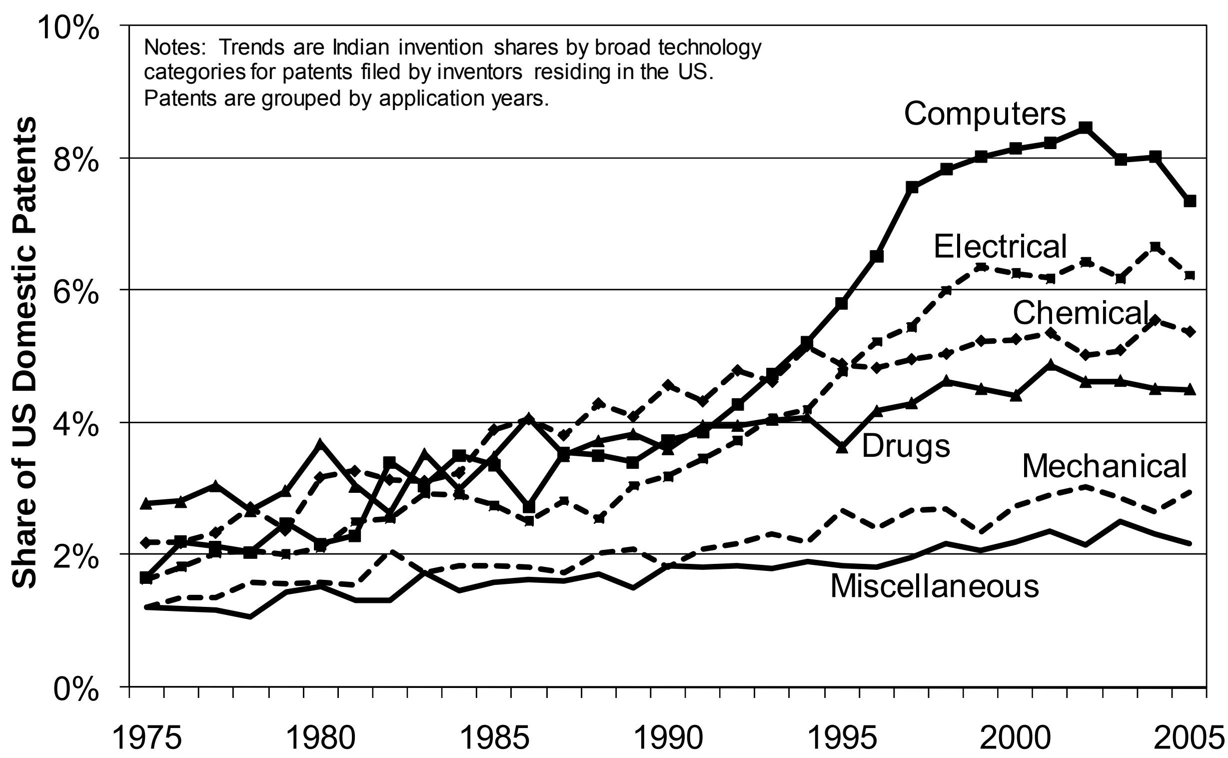

Fig. 3: Chinese Contribution by Technology

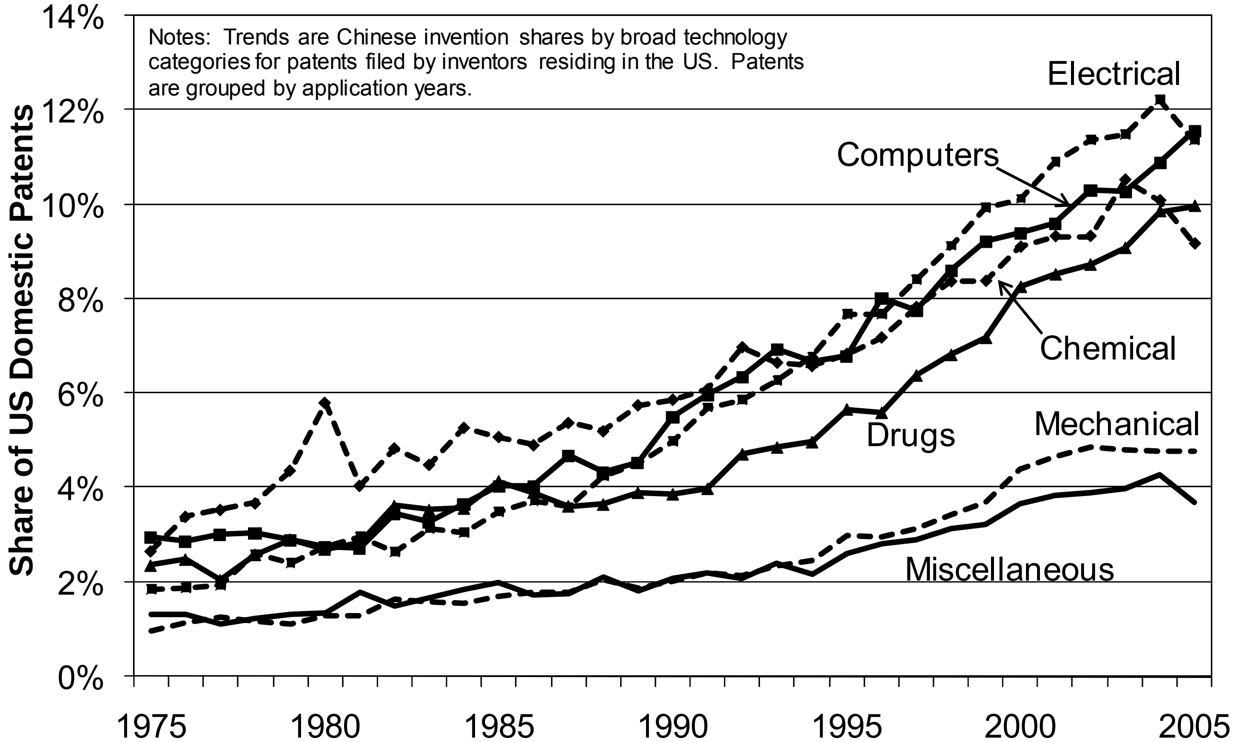

Fig. 4: H-1B Visas and Population Estimates

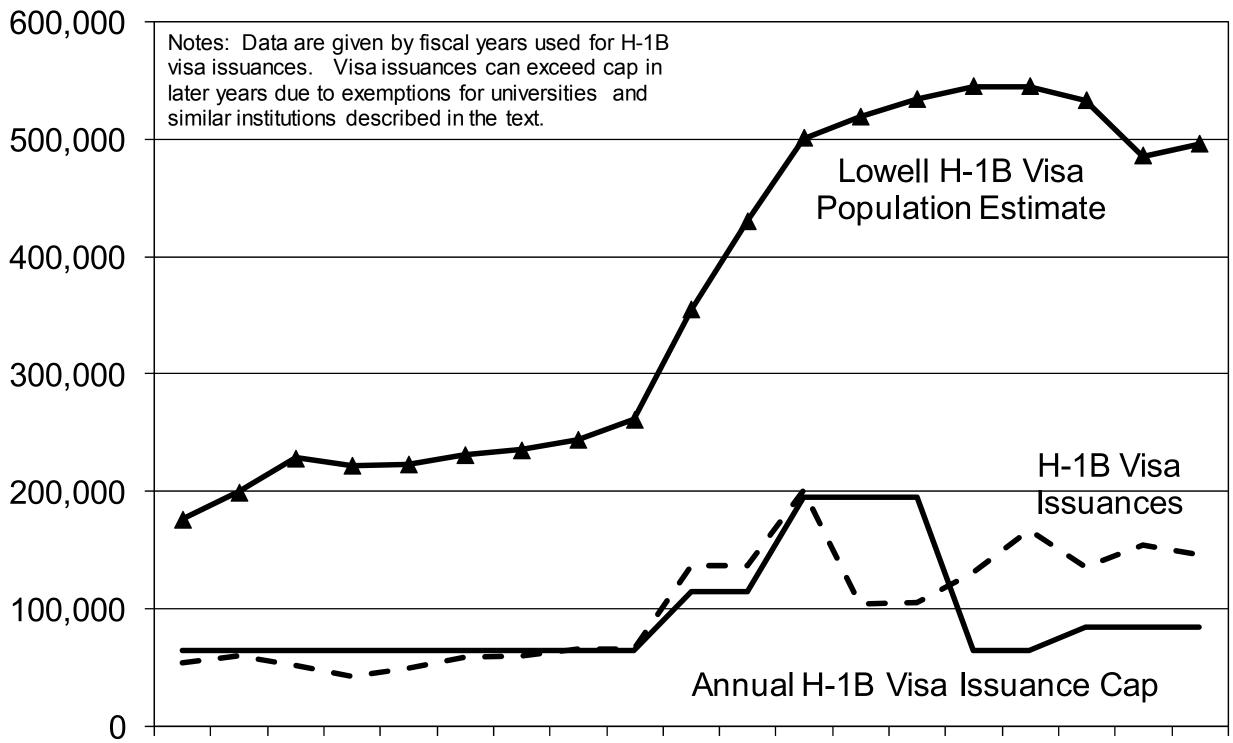

Fig. 5: Indian and Chinese Share by Firm

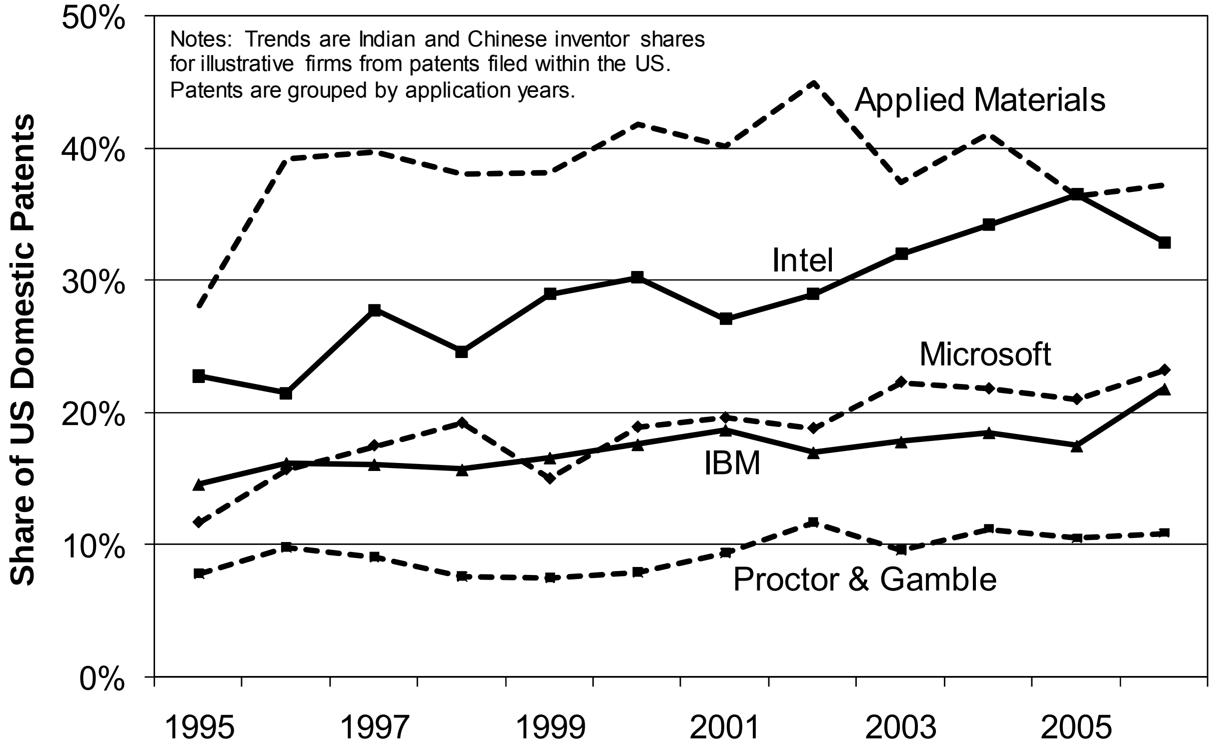

Table 1: Descriptive Statistics for Inventors Residing in US

	Ethnicity of Inventor								
	English	Chinese	European	Hispanic	Indian	Japanese	Korean	Russian	Vietnam.
	A. Ethnic Inventor Shares Estimated from US Inventor Records, 1975-2004								
1975-1979	82.5%	2.2%	8.3%	2.9%	1.9%	0.6%	0.3%	1.2%	0.1%
1980-1984	81.1%	2.9%	7.9%	3.0%	2.4%	0.7%	0.5%	1.3%	0.1%
1985-1989	79.8%	3.6%	7.5%	3.2%	2.9%	0.8%	0.6%	1.4%	0.2%
1990-1994	77.6%	4.6%	7.2%	3.5%	3.6%	0.9%	0.7%	1.5%	0.4%
1995-1999	73.9%	6.5%	6.8%	3.9%	4.8%	0.9%	0.8%	1.8%	0.5%
2000-2004	70.4%	8.5%	6.4%	4.2%	5.4%	1.0%	1.1%	2.2%	0.6%
Chemicals	73.4%	7.2%	7.5%	3.6%	4.5%	1.0%	0.8%	1.7%	0.3%
Computers	70.1%	8.2%	6.3%	3.8%	6.9%	1.1%	0.9%	2.1%	0.7%
Pharmaceuticals	72.9%	7.1%	7.4%	4.3%	4.2%	1.1%	0.9%	1.8%	0.4%
Electrical	71.6%	8.0%	6.8%	3.7%	4.9%	1.1%	1.1%	2.1%	0.7%
Mechanical	80.4%	3.2%	7.1%	3.5%	2.6%	0.7%	0.6%	1.6%	0.2%
Miscellaneous	81.3%	2.9%	7.0%	3.8%	2.1%	0.6%	0.6%	1.4%	0.3%
Top Cities as a	KC (89)	SF (13)	NOR (12)	MIA (16)	SF (7)	SD (2)	BAL (2)	BOS (3)	AUS (2)
Percentage of	WS (88)	LA (8)	STL (11)	SA (9)	AUS (7)	SF (2)	LA (2)	NYC (3)	SF (1)
City's Patents	NAS (88)	AUS (6)	NYC (11)	WPB (7)	PRT (6)	LA (2)	SF (1)	SF (3)	LA (1)
	B. Ethnic Scientist and Engineer Shares Estimated from 1990 US Census Records								
Bachelors Share	87.6%	2.7%	2.3%	2.4%	2.3%	0.6%	0.5%	0.4%	1.2%
Masters Share	78.9%	6.7%	3.4%	2.2%	5.4%	0.9%	0.7%	0.8%	1.0%
Doctorate Share	71.2%	13.2%	4.0%	1.7%	6.5%	0.9%	1.5%	0.5%	0.4%

Notes: Panel A presents descriptive statistics for inventors residing in the US at the time of patent application. Inventor ethnicities are estimated through inventors' names using techniques described in the text. Patents are grouped by application years and major technology fields. Cities, defined through Metropolitan Statistical Areas, include AUS (Austin), BAL (Baltimore), BOS (Boston), KC (Kansas City), LA (Los Angeles), MIA (Miami), NAS (Nashville), NOR (New Orleans), NYC (New York City), PRT (Portland), SA (San Antonio), SD (San Diego), SF (San Francisco), STL (St. Louis), WPB (West Palm Beach), and WS (Winston-Salem). Cities are identified from inventors' city names using city lists collected from the Office of Social and Economic Data Analysis at the University of Missouri, with a matching rate of 99%. Manual recoding further ensures all patents with more than 100 citations and all city names with more than 100 patents are identified. Panel B presents comparable statistics calculated from the 1990 Census using country of birth for scientists and engineers. Country groupings follow Kerr (2007); English provides a residual in the Census statistics.

Table 2: City-Year Correlations of English and Indian/Chinese Patenting

	City & Year Fixed Effects	Column (1) plus Expected Patenting Trends	Column (2) plus State-Year Fixed Effects	Column (2) plus Population Weights	Column (2) plus Dropping Largest 20% of Cities
	(1)	(2)	(3)	(4)	(5)
			A. Log English Patenting		
Log Indian and Chinese Ethnic Patenting	0.137	0.099	0.079	0.127	0.097
	(0.024)	(0.020)	(0.021)	(0.023)	(0.022)
			B. Log Total Patenting		
Log Indian and Chinese Ethnic Patenting	0.211	0.172	0.158	0.202	0.176
	(0.022)	(0.018)	(0.019)	(0.023)	(0.020)

Notes: City-year regressions consider 1995-2006 with 3372 observations. Column 5 contains 2700 observations. Regressions contain city and year fixed effects, are unweighted excepting Column 4, and cluster standard errors by city. The appendix extends this analysis.

Table 3: Most-Dependent Cities on H-1B Program

	LCA-Based Dependency City's 2001-2002 LCA Filings for H-1B Visas Per Capita (x1000)		Census-Based Dependency City's 1990 Non-Citizen Immigrant SE Workforce per Capita (x1000)	
	(1)		(2)	
#1	San Francisco, CA	8.323	Lafayette-W. Lafayette, IN	7.810
#2	Miami, FL	5.502	Bryan-College Station, TX	5.571
#3	Washington, DC	5.430	San Francisco, CA	5.096
#4	Raleigh-Durham, NC	5.220	Columbia, MO	4.462
#5	Boston, MA	5.149	Gainesville, FL	4.146
#6	Austin, TX	4.897	Champaign-Urbana-Rantoul, IL	4.023
#7	New York, NY	4.777	Washington, DC	3.168
#8	Burlington, VT	4.491	Boston, MA	3.129
#9	Atlanta, GA	4.116	Raleigh-Durham, NC	2.723
#10	Dallas-Fort Worth, TX	3.943	Los Angeles, CA	2.288
#11	Champaign-Urbana-Rantoul, IL	3.819	Rochester, MN	2.247
#12	Iowa City, IA	3.804	New York, NY	2.185
#13	Houston, TX	3.712	Houston, TX	2.156
#14	Bryan-College Station, TX	3.577	Spokane, WA	2.078
#15	Seattle, WA	3.393	State College, PA	2.058
#16	Charlottesville, VA	3.310	Pittsfield, MA	2.056
#17	San Diego, CA	3.021	San Diego, CA	2.040
#18	Los Angeles, CA	2.811	Cumberland, MD	1.884
#19	Bloomington-Normal, IL	2.792	Austin, TX	1.770
#20	West Palm Beach, FL	2.744	Fort Collins-Loveland, CO	1.755

Notes: Table presents largest dependency values on the H-1B program. The appendix documents dependencies for all major patenting cities.

Table 4A: City-Year Regressions of H-1B Program Dependency and US Invention

	Log Indian Patenting	Log Chinese Patenting	Log Other Ethnicity Patenting	Log English Patenting	Log Total Patenting
	(1)	(2)	(3)	(4)	(5)
			A. LCA-Based Dependency		
Log National H-1B Population x					
Third Dependency Quintile [LCA]	0.313	0.311	0.305	-0.010	0.037
	(0.087)	(0.095)	(0.106)	(0.101)	(0.107)
Second Dependency Quintile [LCA]	0.623	0.741	0.461	0.050	0.078
	(0.090)	(0.108)	(0.096)	(0.087)	(0.083)
Most Dependent Quintile [LCA]	0.982	1.179	0.593	0.109	0.172
	(0.078)	(0.091)	(0.092)	(0.086)	(0.086)
			B. Census-Based Dependency		
Log National H-1B Population x					
Third Dependency Quintile [Census]	0.207	0.569	0.134	0.048	0.064
	(0.104)	(0.123)	(0.109)	(0.097)	(0.099)
Second Dependency Quintile [Census]	0.398	0.489	0.285	0.064	0.080
	(0.096)	(0.115)	(0.103)	(0.100)	(0.098)
Most Dependent Quintile [Census]	0.550	0.718	0.215	-0.019	0.029
	(0.097)	(0.109)	(0.101)	(0.081)	(0.083)

Notes: City-year regressions consider 1995-2006. Regressions include city and year fixed effects, have 3372 observations, are unweighted, and cluster standard errors by city. Cities are grouped into quintiles based upon indicated H-1B dependency estimate. The H-1B population regressor is interacted with binary indicator variables for the top three dependency quintiles to measure effects relative to the bottom two quintiles, as in equation (2) in the text.

Table 4B: City-Year Regressions Including Ethnic-Specific Technology Trends

	Log Indian Patenting	Log Chinese Patenting	Log Other Ethnicity Patenting	Log English Patenting	Log Total Patenting
	(1)	(2)	(3)	(4)	(5)
	A. LCA-Based Dependency				
Log National H-1B Population x					
Third Dependency Quintile [LCA]	0.172	0.154	0.210	0.043	0.103
	(0.088)	(0.086)	(0.102)	(0.074)	(0.077)
Second Dependency Quintile [LCA]	0.362	0.455	0.285	0.105	0.162
	(0.089)	(0.113)	(0.097)	(0.077)	(0.075)
Most Dependent Quintile [LCA]	0.552	0.714	0.338	0.164	0.266
	(0.098)	(0.106)	(0.098)	(0.081)	(0.079)
Log Predicted Indian Patents	0.345	0.393	0.035	-0.140	-0.087
in City due to Tech Trends	(0.075)	(0.091)	(0.093)	(0.071)	(0.065)
Log Predicted Chinese Patents	0.135	0.104	0.037	0.049	-0.010
in City due to Tech Trends	(0.063)	(0.075)	(0.088)	(0.069)	(0.065)
Log Predicted Other Ethnicity Patents	0.022	0.079	0.343	-0.118	-0.168
in City due to Tech Trends	(0.043)	(0.041)	(0.068)	(0.063)	(0.063)
Log Predicted English Patents	-0.019	-0.040	0.036	0.658	0.693
in City due to Tech Trends	(0.021)	(0.020)	(0.032)	(0.046)	(0.048)
	B. Census-Based Dependency (Ethnic-Specific Technology Trends Not Reported)				
Log National H-1B Population x					
Third Dependency Quintile [Census]	0.067	0.412	0.049	0.014	0.027
	(0.087)	(0.106)	(0.098)	(0.081)	(0.082)
Second Dependency Quintile [Census]	0.105	0.162	0.112	0.056	0.079
	(0.085)	(0.101)	(0.095)	(0.076)	(0.072)
Most Dependent Quintile [Census]	0.139	0.256	-0.014	0.006	0.059
	(0.080)	(0.089)	(0.092)	(0.072)	(0.073)

Notes: See Table 4A. Panel B includes unreported ethnic-specific technology trends similar to Panel A.

Table 5: City-Year Lag Structure Tests

	Δ Log Indian Patenting	Δ Log Chinese Patenting	Δ Log Other Ethnicity Patenting	Δ Log English Patenting	Δ Log Total Patenting
	(1)	(2)	(3)	(4)	(5)
Forward					
[Log H-1B Pop (t+2) - Log H-1B Pop (t)] x	0.060	0.077	0.114	-0.044	-0.019
Third Dependency Quintile [LCA]	(0.088)	(0.079)	(0.109)	(0.095)	(0.094)
[Log H-1B Pop (t+2) - Log H-1B Pop (t)] x	-0.017	0.000	-0.034	-0.037	-0.041
Second Dependency Quintile [LCA]	(0.080)	(0.088)	(0.099)	(0.085)	(0.084)
[Log H-1B Pop (t+2) - Log H-1B Pop (t)] x	0.128	0.161	-0.015	-0.073	-0.033
Most Dependent Quintile [LCA]	(0.084)	(0.094)	(0.089)	(0.083)	(0.083)
Contemporaneous					
[Log H-1B Pop (t) - Log H-1B Pop (t-2)] x	0.013	0.110	0.091	0.073	0.064
Third Dependency Quintile [LCA]	(0.122)	(0.111)	(0.143)	(0.134)	(0.129)
[Log H-1B Pop (t) - Log H-1B Pop (t-2)] x	0.264	0.266	0.373	0.080	0.093
Second Dependency Quintile [LCA]	(0.110)	(0.120)	(0.141)	(0.117)	(0.107)
[Log H-1B Pop (t) - Log H-1B Pop (t-2)] x	0.218	0.448	0.344	0.199	0.158
Most Dependent Quintile [LCA]	(0.096)	(0.112)	(0.121)	(0.115)	(0.109)
Lagged					
[Log H-1B Pop (t-2) - Log H-1B Pop (t-4)] x	0.155	-0.035	-0.027	-0.040	-0.027
Third Dependency Quintile [LCA]	(0.097)	(0.077)	(0.109)	(0.094)	(0.086)
[Log H-1B Pop (t-2) - Log H-1B Pop (t-4)] x	0.039	0.096	-0.132	-0.040	-0.035
Second Dependency Quintile [LCA]	(0.080)	(0.095)	(0.098)	(0.079)	(0.069)
[Log H-1B Pop (t-2) - Log H-1B Pop (t-4)] x	0.177	-0.027	-0.058	-0.118	-0.071
Most Dependent Quintile [LCA]	(0.063)	(0.076)	(0.074)	(0.071)	(0.064)

Notes: See Table 4A.

Table 6: Comparison of US and Canadian Cities

	Log Indian Patenting	Log Chinese Patenting	Log Other Ethnicity Patenting	Log English Patenting	Log Total Patenting
	(1)	(2)	(3)	(4)	(5)
	A. US Sample of Cities				
Log US National H-1B Population x Most Dependent Half [US Census]	0.411	0.538	0.207	-0.014	0.026
	(0.072)	(0.084)	(0.077)	(0.068)	(0.069)
Observations	3372	3372	3372	3372	3372
	B. US Sample of Cities, Removing Top Quintile of US Cities				
Log US National H-1B Population x Most Dependent Half [US Census]	0.298	0.522	0.203	0.052	0.068
	(0.079)	(0.090)	(0.088)	(0.079)	(0.080)
Observations	2700	2700	2700	2700	2700
	C. Canadian Sample of Cities				
Log US National H-1B Population x Most Dependent Half [CAN Census]	-0.228	0.037	-0.085	-0.135	-0.043
	(0.174)	(0.226)	(0.178)	(0.181)	(0.174)
Observations	588	588	588	588	588
	D. Canadian Sample of Cities, Without Province-Level Dependencies				
Log US National H-1B Population x Most Dependent Half [CAN Census]	-0.174	-0.038	0.125	0.078	0.025
	(0.271)	(0.360)	(0.233)	(0.195)	(0.220)
Observations	264	264	264	264	264

Notes: City-year regressions consider 1995-2006. Canadian cities are those for which pseudo-dependencies can be calculated from the 1990 Canadian Census. The top US dependency quintile is removed in Panel B as the maximum dependency in the Canadian sample falls in the second US dependency quintile. Panel D drops Canadian cities for which we can only determine province-level dependency rates. Regressions include city and year fixed effects, are unweighted, and cluster standard errors by city. Cities are grouped into upper and lower halves for each country based upon dependency estimates. The H-1B population regressor is interacted with a binary indicator variable for being in the upper half of the distribution. Coefficient estimates are relative to the lower half of the distribution.

Table 7: CPS Regressions of H-1B Program Dependency

	States with Measured Immigrant SE Workers				All States	
	Δ Log non-Citizen Immigrant SE Workers	Δ Log Immigrant SE Workers	Δ Log Native SE Workers	Δ Log Total SE Workers	Δ Log Native SE Workers	Δ Log Total SE Workers
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Correlations of non-Citizen Immigrant Growth and Native Inventor Growth					
Δ Log non-Citizen Immigrant SE Workers			0.016	0.085		
			(0.018)	(0.015)		
	B Correlations of Total Immigrant Growth and Native Inventor Growth					
Δ Log Immigrant SE Workers			0.046	0.157		
			(0.022)	(0.019)		
	C. Reduced-Form Estimations with LCA-Based Dependency					
Δ Log National H-1B Population x Most Dependent Half [LCA]	0.485	0.294	0.103	0.159	0.142	0.196
	(0.301)	(0.369)	(0.150)	(0.114)	(0.077)	(0.074)
	D. Reduced-Form Estimations with Census-Based Dependency					
Δ Log National H-1B Population x Most Dependent Half [Census]	0.742	0.448	-0.063	0.037	0.055	0.101
	(0.327)	(0.388)	(0.150)	(0.112)	(0.080)	(0.078)
Observations	260	260	260	260	510	510

Notes: State-year regressions consider 1995-2006 through first-differenced specifications. Changes from 2002-2003 are excluded due to the redesign of the CPS in 2003. Regressions include year fixed effects, are unweighted, and cluster standard errors by state. Columns 1-4 restrict the CPS sample to the 26 states that report immigrant SE populations in each year from 1995-2006. Columns 5 and 6 use all states and the District of Columbia.

Table 8: Descriptive Statistics for Firm Panel

	Median	Mean	Stand. Dev.	Minimum	Maximum	US Totals
Firm-Level Patenting						
Annual Patent Count	57	132	238	0.1	2098	
Indian Inventors	4%	6%	5%	0%	26%	5%
Chinese Inventors	7%	8%	6%	0%	41%	8%
Other Ethnic Inventors	15%	16%	7%	0%	50%	15%
English Inventors	73%	71%	13%	39%	96%	72%
Chemicals	5%	13%	18%	0%	76%	13%
Computers & Communications	18%	33%	34%	0%	100%	23%
Drugs & Medical	0%	9%	21%	0%	89%	11%
Electrical & Electronic	10%	17%	20%	0%	98%	19%
Mechanical	7%	15%	18%	0%	93%	17%
Miscellaneous	5%	13%	19%	0%	99%	17%
New England	2%	7%	15%	0%	93%	8%
Middle Atlantic	0%	15%	26%	0%	95%	15%
East North Central	2%	17%	29%	0%	100%	16%
West North Central	0%	6%	18%	0%	100%	6%
South Atlantic	2%	8%	18%	0%	100%	10%
East South Central	0%	3%	14%	0%	100%	2%
West South Central	1%	9%	21%	0%	97%	8%
Mountain	1%	7%	18%	0%	98%	7%
Pacific	7%	28%	35%	0%	100%	28%
Firm-Level LCA Applications						
Annual LCA Count	40	117	239	0	2254	
Firm-Level Compustat Activity						
Annual Sales	5,001	16,719	28,737	4	166,383	
Annual Employees	22	54	85	0	611	
Annual R&D	166	721	1,274	0	7,716	

Notes: Compustat Sales and R&D expenditures are in millions of dollars. Compustat Employees figures are in thousands of employees.

Table 9: Firm Characteristics and Ethnic Inventor Shares

	Ethnic Shares of Firm's Patenting			
	Indian	Chinese	Other Ethnicities	English
	(1)	(2)	(3)	(4)
Log of Mean Annual Patents	0.009	0.006	-0.012	-0.003
	(0.002)	(0.003)	(0.004)	(0.006)
Log of Mean Annual Sales	-0.001	-0.002	0.012	-0.009
	(0.002)	(0.003)	(0.003)	(0.005)
Technology Shares of Firm Patents (Other/Miscellaneous Category omitted):				
Chemicals	0.031	0.114	-0.030	-0.115
	(0.024)	(0.034)	(0.039)	(0.061)
Computers & Communications	0.047	0.076	0.011	-0.134
	(0.016)	(0.022)	(0.026)	(0.041)
Drugs & Medical	-0.006	0.082	-0.001	-0.075
	(0.020)	(0.028)	(0.032)	(0.050)
Electrical & Electronic	0.045	0.130	0.007	-0.182
	(0.021)	(0.029)	(0.034)	(0.054)
Mechanical	-0.023	0.041	-0.026	0.007
	(0.025)	(0.035)	(0.040)	(0.063)
Regional Shares of Firm Patents (East South Central omitted):				
New England	0.028	0.044	0.111	-0.183
	(0.029)	(0.040)	(0.047)	(0.074)
Middle Atlantic	0.051	0.060	0.094	-0.205
	(0.024)	(0.035)	(0.040)	(0.063)
East North Central	0.015	0.022	0.059	-0.096
	(0.025)	(0.035)	(0.041)	(0.065)
West North Central	-0.001	0.030	-0.013	-0.016
	(0.027)	(0.038)	(0.044)	(0.069)
South Atlantic	0.016	0.063	0.099	-0.179
	(0.029)	(0.041)	(0.047)	(0.075)
West South Central	0.041	0.050	0.074	-0.165
	(0.026)	(0.037)	(0.043)	(0.068)
Mountain	0.020	0.007	0.058	-0.084
	(0.028)	(0.039)	(0.046)	(0.072)
Pacific	0.057	0.091	0.136	-0.284
	(0.023)	(0.033)	(0.038)	(0.060)
Constant	-0.035	-0.053	0.019	1.070
	(0.029)	(0.041)	(0.047)	(0.074)
Overall R^2	0.45	0.39	0.35	0.53
R^2 with only sales and patents	0.10	0.07	0.06	0.02
R^2 with only technology categories	0.25	0.25	0.08	0.26
R^2 with only geographic areas	0.25	0.24	0.21	0.41

Notes: Firm-level regressions consider averages over 1995-2004 period. Regressions are unweighted.

Table 10: Firm-Year Regressions of H-1B Dependency by Sector

	Log Indian Patenting	Log Chinese Patenting	Log Other Ethnicity Patenting	Log English Patenting	Log Total Patenting
	(1)	(2)	(3)	(4)	(5)
Log National H-1B Population x					
More Dependent Half of	0.782	0.416	0.671	0.136	0.399
Computer-Oriented Firms	(0.338)	(0.465)	(0.355)	(0.320)	(0.323)
Less Dependent Half of	0.152	-0.157	0.073	0.036	0.048
Computer-Oriented Firms	(0.221)	(0.396)	(0.243)	(0.236)	(0.233)
More Dependent Half of	0.184	0.134	0.175	0.153	0.208
non-Computer-Oriented Firms	(0.248)	(0.326)	(0.241)	(0.189)	(0.194)
Log Predicted Firm Patents	0.800	0.744	0.745	0.716	0.733
due to Technology Trends	(0.152)	(0.164)	(0.155)	(0.131)	(0.126)

Notes: Firm-year regressions consider 1995-2006. Regressions include firm and year fixed effects, have 972 observations, are unweighted, and cluster standard errors by firm. Firms are divided into computer-oriented firms and those outside the computer sector through each firm's most frequent patent category. Regressions interact national H-1B population changes with an indicator variable for more dependent computer firms, less dependent computer firms, and more dependent non-computer firms. Effects are measured relative less dependent firms outside of the computer sector.