

09-003

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The Agglomeration of US Ethnic Inventors

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16 July 2008
HBS Working Paper 09-003

Abstract

The ethnic composition of US inventors is undergoing a significant transformation — with deep impacts for the overall agglomeration of US innovation. This study applies an ethnic-name database to individual US patent records to explore these trends with greater detail. The contributions of Chinese and Indian scientists and engineers to US technology formation increase dramatically in the 1990s. At the same time, these ethnic inventors became more spatially concentrated across US cities. The combination of these two factors helps stop and reverse long-term declines in overall inventor agglomeration evident in the 1970s and 1980s. The heightened ethnic agglomeration is particularly evident in industry patents for high-tech sectors, and similar trends are not found in institutions constrained from agglomerating (e.g., universities, government).

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

Key Words: Agglomeration, Innovation, Research and Development, Patents, Scientists, Engineers, Inventors, Ethnicity, Immigration.

*Comments are appreciated and can be sent to wkerr@hbs.edu. This paper is a forthcoming book chapter in the *Economics of Agglomeration* edited by Ed Glaeser. I am grateful to William Lincoln and Debbie Strumsky for data assistance. I thank Ed Glaeser, Jeff Furman, and participants in the Economics of Agglomeration conferences for helpful comments and research ideas. This research is supported by Harvard Business School, the National Science Foundation, the Innovation Policy and the Economy Group, and the MIT George Schultz Fund.

1 Introduction

Economists have long been interested in agglomeration and innovation. In his seminal outline of the core rationales for industrial clusters, Marshall (1920) emphasized the theory of intellectual spillovers by arguing that in agglomerations, "the mysteries of the trade become no mystery, but are, as it were, in the air." Workers can learn skills quickly from each other in an industrial cluster, and this proximity can speed the adoption of new technologies or best practices. Glaeser and Kahn (2001) argue that the urbanization of high human-capital industries, like finance, is evidence for the role that density plays in the transfer of ideas, and studies of patent citations highlight the importance of local proximity for scientific exchanges (e.g., Jaffe et al. 1992, Thompson and Fox-Kean 2006). Moreover, evidence suggests that agglomeration increases the rate of innovation itself. Saxenian (1994) describes how entrepreneurial firms locate near one another in Silicon Valley to foster new technology development. Carlino et al. (2006) show that higher urban employment density is correlated with greater patenting per capita within cities.

Strong quantitative assessments of the magnitudes and characteristics of intellectual spillovers and agglomeration are essential. Such studies inform business managers of the advantages and costs for locating in areas that are rich in ideas but most likely come with higher rents and wages as well. Moreover, these studies are important for understanding short-run and long-run urban growth and development. They help inform whether industrial specialization or diversity better foster regional development (e.g., Jacobs 1970, Glaeser et al. 1992, Henderson et al. 1995, Duranton and Puga 2001, Duranton 2007) and the role of local knowledge development and externalities in generating sustained growth (e.g., Romer 1986, 1990, Furman et al. 2002). Rosenthal and Strange (2003) note that intellectual spillovers are strongest at the very local levels of proximity.¹

This study contributes to our empirical understanding of agglomeration and innovation by documenting patterns in the city-level agglomeration of ethnic inventors (e.g., Chinese, Indian) within the US from 1975 through 2007. The contributions of these immigrant groups to US technology formation are staggering: while foreign-born account for just over 10% of the US working population, they represent 25% of the US science and engineering (SE) workforce and nearly 50% of those with doctorates. Even looking within the Ph.D. level, ethnic researchers make exceptional contributions to science as measured by Nobel Prizes, elections to the National Academy of Sciences, patent citation counts, and so on.² Recent work relates immigration and growth in US invention (e.g., Peri 2007, Hunt 2008, Kerr and Lincoln 2008). Moreover, ethnic

¹Several studies assess the relative importance of intellectual spillovers versus other rationales for industrial agglomeration (e.g., lower transportation costs, labor market pooling). Representative papers include Audretsch and Feldman (1996), Rosenthal and Strange (2001), Henderson (2003), and Ellison et al. (2007). Porter (1990) emphasizes how vertically related industries may co-locate for knowledge sharing.

²For example, Stephan and Levin (2001), Burton and Wang (1999), Johnson (1998, 2001), and Streeter (1997).

entrepreneurs are very active in commercializing new technologies, especially in high-tech sectors (e.g., Saxenian 2002a, Wadhwa et al. 2007).

The spatial distribution of ethnic inventors across US cities, however, is far from random. Immigrants tend to concentrate in certain US cities, often the largest ones that offer the greatest opportunities for assimilation. Geographical distances of cities to home countries and past immigration networks are also important for location decisions.³ The study of US ethnic inventors is thus very important given 1) the disproportionate contributions of immigrant researchers and 2) their non-random spatial distribution across the US. Such a characterization is necessary for understanding the geography of US innovation and economic growth. Moreover, the spatial variation of immigrant researchers across cities allows for stronger quantitative assessments of the role of innovation in city growth. This paper is a first step in this direction.

Econometric studies quantifying the role of ethnic scientists and engineers for technology formation and diffusion are often hampered, however, by data constraints. It is very difficult to assemble sufficient cross-sectional and longitudinal variation for large-scale panel exercises.⁴ This paper describes a new approach for quantifying the ethnic composition of US inventors with previously unavailable detail. The technique exploits the inventor names contained on the micro-records for all patents granted by the United States Patent and Trademark Office (USPTO) from January 1975 to April 2007.⁵ Each patent record lists one or more inventors, with 7.5 million inventor names associated with the 4.3 million patents. The USPTO grants patents to inventors living within and outside of the US, with each group accounting for about half of patents over the 1975-2007 period.

This study maps into these inventor names an ethnic-name database typically used for commercial applications. This approach exploits the idea that inventors with the surnames Chang or Wang are likely of Chinese ethnicity, those with surnames Rodriguez or Martinez of Hispanic ethnicity, and so on. The match rates are 92%-98% for US domestic inventor records, depending upon the procedure employed, and the process affords the distinction of nine ethnicities: Chinese, English, European, Hispanic/Filipino, Indian/Hindi, Japanese, Korean, Russian, and Vietnamese. Moreover, because the matching is done at the micro-level, greater detail on the ethnic composition of inventors is available annually on multiple dimensions: technologies, cities, companies, and so on. Section 2 describes this data development in greater detail.

³For example, Borjas (1994), Friedberg and Hunt (1995), Freeman (2006), and Kerr and Kerr (2008).

⁴While the decennial Census provides detailed cross-sectional descriptions, its longitudinal variation is necessarily limited. The annual Current Population Survey, however, provides poor cross-sectional detail and does not ask immigrant status until 1994. The SESTAT database offers a better trade-off between the two dimensions, but suffers important sampling biases with respect to immigrants (Kannankutty and Wilkinson 1999).

⁵The project initially employed the NBER Patent Data File, compiled by Hall et al. (2001), that includes patents granted by the USPTO from January 1975 to December 1999. The current version now employs an extended version developed by HBS Research that includes patents granted through early 2007.

Section 3 then documents the growing contribution of ethnic inventors to US technology formation. The rapid increase during the 1990s in the share of high-tech patents granted to Chinese and Indian inventors is particularly striking. This section also uses the patenting data to calculate concentration indices for US innovation. Ethnic inventors have higher levels of spatial concentration than English inventors throughout the thirty-year period studied. Moreover, the spatial concentration of ethnic inventors increases significantly from 1995 to 2004, especially in high-tech sectors like computer-related patenting. The combination of greater ethnic shares and increasing agglomeration of ethnic inventors helps stop and reverse the 1975-1994 declines in the overall concentration of US invention. These trends are confined to industrial patents; universities and government bodies — that are constrained from agglomerating — do not show recent increases in spatial clustering.

The final section concludes. The higher agglomeration of immigrants in cities and occupations has long been noted. For example, Mandorff (2007) highlights how immigrant entrepreneurs tend to agglomerate in selected industries, a process that increases their business impact for specific sectors. Examples within the US are Korean entrepreneurs in dry cleaning, Vietnamese in nail salons, Gujarati Indians in traveler accommodations, Punjabi Indians in gas stations, Greeks in restaurants, and so on. The higher natural social interactions among these ethnic groups aid in the acquisition and transfer of sector-specific skills; scale economies lead to occupational clustering by minority ethnic groups.

To date, there has been very little work, theoretically or empirically, on the agglomeration of US ethnic scientists and engineers with the notable exception of Agrawal et al. (2007).⁶ This scarcity of research is disappointing given the scale of these ethnic contributions and the importance of innovation to regional economic growth. Moreover, the large shifts in ethnic inventor populations, often driven in part by US immigration restrictions, may provide empirical footholds for testing agglomeration theories in a natural experiment framework. It is hoped that the empirical platform developed in this study provides a foothold for furthering such analyses.

2 Ethnic-Name Matching Technique

This section describes the ethnic-name matching strategy, outlines the strengths and weaknesses of the name database selected, and offers some validation exercises using patent records filed by foreign inventors with the USPTO. Kerr (2007) further describes the name-matching process,

⁶Agrawal et al. (2007) jointly examine knowledge diffusion through co-location and co-ethnicity using domestic patent citations made by Indian inventors living in the US. While being in the same city or the same ethnicity both encourage knowledge diffusion, their estimations suggest that the marginal benefit of co-location is four times larger for inventors of different ethnicities. This substitutability between social and geographic proximity can create differences between a social planner's optimal distribution of ethnic members and what the inventors themselves would choose.

the international name distribution technique, and the apportionment of non-unique matches that are highlighted below.

2.1 Melissa Ethnic-Name Database and Name-Matching Technique

The ethnic-name database employed in this study was originally developed by the Melissa Data Corporation for use in direct-mail advertisements. Ethnic-name databases suffer from two inherent limitations — not all ethnicities are covered and included ethnicities usually receive unequal treatment. The strength of the Melissa database is in the identification of Asian ethnicities, especially Chinese, Indian/Hindi, Japanese, Korean, Russian, and Vietnamese names. The database is comparatively weaker for looking within continental Europe. For example, Dutch surnames are collected without first names, while the opposite is true for French names. The Asian comparative advantage and overall cost effectiveness led to the selection of the Melissa database, as well as the European amalgamation employed in the matching technique. In total, nine ethnicities are distinguished: Chinese, English, European, Hispanic/Filipino, Indian/Hindi, Japanese, Korean, Russian, and Vietnamese.⁷

The second limitation is that commercial databases vary in the number of names they contain for each ethnicity. These differences reflect both uneven coverage and that some ethnicities are more homogeneous in their naming conventions. For example, the 1975 to 1999 Herfindahl indices of foreign inventor surnames for Korean (0.047) and Vietnamese (0.112) are significantly higher than Japanese (0.013) and English (0.016) due to frequent Korean surnames like Kim (16%) and Park (12%) and Vietnamese surnames like Nguyen (29%) and Tran (12%).

Two polar matching strategies are employed to ensure coverage differences do not overly influence ethnicity assignments.

Full Matching: This procedure utilizes all of the name assignments in the Melissa database and manually codes any unmatched surname or first name associated with 100 or more inventor records. This technique further exploits the international distribution of inventor names within the patent database to provide superior results. The match rate for this restricted procedure is 97% (98% US, 97% foreign). This rate should be less than 100% with the Melissa database as not all ethnicities are included.

Restricted Matching: A second strategy employs a uniform name database using only the 3000 and 200 most common surnames and first names, respectively, for each

⁷The largest ethnicity in the US SE workforce absent from the ethnic-name database is Iranian, which accounted for 0.7% of bachelor-level SEs in the 1990 Census.

ethnicity. These numerical bars are the lowest common denominators across the major ethnicities studied. The match rate for this restricted procedure is 88% (92% US, 86% foreign).

For matching, names in both the patent and ethnic-name databases are capitalized and truncated to ten characters. Approximately 88% of the patent name records have a unique surname, first name, or middle name match in the Full Matching procedure (77% in the Restricted Matching), affording a single ethnicity determination with priority given to surname matches. For inventors residing in the US, representative probabilities are assigned to non-unique matches using the masters-level SE communities in Metropolitan Statistical Areas (MSAs). Ethnic probabilities for the remaining 3% of records (mostly foreign) are calculated as equal shares.

2.2 Inventors Residing in Foreign Countries and Regions

Visual confirmation of the top 1000 surnames and first names in the USPTO records confirms the name-matching technique works well. The appendix documents the fifty most common surnames of US-based inventors for each ethnicity, along with their relative contributions. While some inventors are certainly misclassified, the measurement error in aggregate trends building from the micro-data is minor. The Full Matching procedure is the preferred technique and underlies the trends presented in the next section, but most applications find negligible differences when the Restricted Matching dataset is employed instead.

The application of the ethnic-name database to the inventors residing outside of the US provides a natural quality-assurance exercise for the technique. Inventions originating outside the US account for just under half of USPTO patents, with applications from Japan comprising about 48% of this foreign total. The appendix documents the results of applying the ethnic-matching procedures for countries and regions grouped to the ethnicities identifiable with the database. The results are very encouraging. First, the Full Matching procedure assigns ethnicities to a large percentage of foreign records, with the match rates greater than 93% for all countries but India (84%). In the Restricted Matching procedure, a matching rate of greater than 73% holds for all regions.

Second, the estimated inventor compositions are reasonable. The weighted average is 86% in the Full Matching procedure, and own-ethnicity contributions are greater than 80% in the UK, China, India, Japan, Korea, and Russia regardless of the matching procedure employed. Like the US, own-ethnicity contributions should be less than 100% due to foreign researchers. The high success rate using the Restricted Matching procedure indicates that the ethnic-name database performs well without exploiting the international distribution of names, although

power is lost with Europe. Likewise, uneven coverage in the Melissa database is not driving the ethnic composition trends.

2.3 Advantages and Disadvantages of Name-Matching Technique

The matched records describe the ethnic composition of US scientists and engineers with previously unavailable detail: incorporating the major ethnicities working in the US SE community; separating out detailed technologies and manufacturing industries; providing metropolitan and state statistics; and providing annual metrics. Moreover, the assignment of patents to corporations and institutions affords firm-level and university-level characterizations that are not otherwise possible (e.g., the ethnic composition of IBM’s inventors filing computer patents from San Francisco in 1985). The next section studies the agglomeration of invention along these various dimensions.⁸

The ethnic-name procedure does, however, have two potential limitations for empirical work on agglomeration that should be highlighted. First, the approach does not distinguish foreign-born ethnic researchers in the US from later generations working as SEs. The procedure can only estimate total ethnic SE populations, and concentration levels are to some extent measured with time-invariant error due to the name-matching approach. The resulting data are very powerful, however, for panel econometrics that employ changes in these ethnic SE populations for identification. Moreover, Census and INS records confirm Asian changes are primarily due to new SE immigration for this period, substantially weakening this concern when examining these groups.

The name-matching technique also does not distinguish finer divisions within the nine major ethnic groupings. For some analyses (e.g., network ties), it would be advantageous to separate Mexican from Chilean scientists within the Hispanic ethnicity, to distinguish Chinese engineers with ethnic ties to Taipei versus Beijing versus Shanghai, and so on. These distinctions are not possible with the Melissa database, and researchers should understand that measurement error from the broader ethnic divisions may bias their estimated coefficients downward depending upon the application. Nevertheless, the upcoming sections demonstrate how the deep variation available with the ethnic patenting data provides a rich description of US ethnic invention.

3 The Agglomeration of US Ethnic Invention

This section starts by describing the broad trends in ethnic contributions to US technology formation. The spatial concentration of ethnic invention is then closely analyzed, including

⁸Sample applications are Kerr (2008a,b), Kerr and Lincoln (2008), and Foley and Kerr (2008).

variations by technology categories and institutions.

3.1 Ethnic Composition of US Inventors

Table 1 describes the ethnic composition of US inventors for 1975-2004, with granted patents grouped by application years. The trends demonstrate a growing ethnic contribution to US technology development, especially among Chinese and Indian 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, European in New York, and Hispanic in Miami). The final three rows demonstrate a close correspondence of the estimated ethnic composition to the country-of-birth composition of the US SE workforce in the 1990 Census. The estimated European contribution in Table 1 is naturally higher than the immigrant contribution measured by foreign born.

Figure 1 illustrates the evolving ethnic composition of US inventors from 1975-2004. The omitted English share declines from 83% to 72% during this period. Looking across all technology categories, the European ethnicity is initially the largest foreign contributor to US technology development. Like the English ethnicity, however, the European share of US domestic inventors declines steadily from 8% in 1975 to 6% in 2004. This declining share is partly due to the exceptional growth over the thirty years of the Chinese and Indian ethnicities, which increase from under 2% to 8% and 4%, respectively. As shown below, this Chinese and Indian growth is concentrated in high-tech sectors, where Chinese inventors supplant European researchers as the largest ethnic contributor to US technology formation. The Indian ethnic contribution declines somewhat after 2000.⁹

Among the other ethnicities, the Hispanic contribution grows from 3% to 5% from 1975 to 2004. The level of this series is likely mismeasured due to the extensive overlap of Hispanic and European names, but the positive growth is consistent with stronger Latino and Filipino scientific contributions in Florida, Texas, and California. The Korean share increases dramatically from 0.3% to 1.3% over the thirty years, while the Russian climbs from 1.3% to 2.2%. Although difficult to see with Figure 1's scaling, much of the Russian increase occurs in the 1990s following the dissolution of the Soviet Union. The Japanese share steadily increases from 0.5% to 1.2%. Finally, while the Vietnamese contribution is the lowest throughout the sample, it does exhibit the strongest relative growth from 0.1% to 0.7%.

The 1975-2004 statistics employ patents granted by the USPTO through March 2007. Due to the long and uneven USPTO review process, statistics are grouped by application year to

⁹This decline is mostly due to changes within the computer technology sector as seen below. Recent applications to the USPTO suggest the Indian trend may not have declined as much as the granted patents through early 2007 portray. Kerr and Lincoln (2008) investigate the role of H-1B visa reforms for explaining these patterns.

construct the most accurate indicators of when inventive activity occurs. The unfortunate consequence of using application years, however, is substantial attrition in years immediately before 2007. As many patents are in the review process but have yet to be granted, the granted patent series is truncated at the 2004 application year. The USPTO began publishing patent applications in 2001. These applications data also show comparable ethnic contributions.

3.2 Spatial Locations of US Ethnic Inventors

Table 2 examines the 1975-2004 ethnic inventor contributions by major MSAs. A total of 283 MSAs 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 coding further ensures all patents with more than 100 citations and all city names with more than 100 patents are identified. The first four columns document each MSA's share of US patenting. Not surprisingly, these shares are highly correlated with MSA size, with the three largest patenting centers for 1995-2004 found in San Francisco (12%), New York (7%), and Los Angeles (6%), where the percentages indicate US domestic patent shares.

Comparing these total patenting percentages with the ethnic patenting shares, listed in the second set of four columns, reveals the more interesting fact that ethnic patenting is more concentrated than general innovation. The 1995-2004 ethnic patent shares of San Francisco, New York, and Los Angeles are 19%, 10%, and 8%, respectively. Similarly, 80% of ethnic research occurs in the major MSAs listed in Table 2, compared to 72% of total patenting. The final three columns list the Chinese patenting share by MSA, highlighting the exceptional growth of San Francisco from 10% of 1975-1984 patenting to 28% in 1995-2004. These concentration levels and trends are further examined below.¹⁰

Table 3 presents simple least squares estimations of ethnic inventor locations and MSA characteristics. The variables of interest are MSA shares of US ethnic inventors during 1985-2004, with column headers indicating ethnicities. These shares are calculated over the 244 MSAs for which full covariate information are assembled. The dropped observations are small cities not separately identified in 1990 Census of Population. For ease of interpretation, variables are transformed to have unit standard deviation in these cross-sectional estimations. Estimations are weighted by MSA populations.

To establish a baseline, the first two columns consider MSA inventor shares of the English ethnicity. In Column 1, MSA size and urban density strongly predict higher English inventor

¹⁰Each of these trends appears to have strengthened in the recent applications data (i.e., the columns marked with A in Table 2). While suggestive, these statistics should be treated with caution. Some technology fields and firm types are more likely to publish their patent applications than others. Likewise, probabilities of patent grants conditional on application vary by field. Lemley and Sampat (2007) discuss these limitations further.

shares. A one standard-deviation increase in the population share of the MSA correlates with a 0.57 standard-deviation increase in the share of English ethnic invention. Coastal access does not predict greater inventor concentration in multi-variate frameworks, although a univariate correlation exists. On the other hand, MSA demographics have a statistically and economically significant relationship with inventor concentrations. The MSA traits are calculated from the 1990 Census of Population. MSAs with more-educated workforces are associated with greater inventor concentrations. Higher shares of English invention are also found in MSAs with relatively more people between the ages of 30 and 60 (the omitted group) and more men. All told, this parsimonious set of covariates explains 84% of the variation in English invention shares.

Table 2 suggests that inventor shares are relatively persistent over time for MSAs. Column 2 of Table 3 confirms this observation for English inventors. The estimation incorporates the share of English ethnic patenting in the MSA for 1975-1984. This ten-year period pre-dates the major growth in ethnic inventors highlighted in Figure 1. The spatial distribution of English invention over 1975-1984 is a very strong predictor for 1985-2004 concentration with an elasticity of 0.84. MSA populations and density levels do not exhibit a well-measured relationship with 1985-2004 English inventor concentrations after controlling for these past levels. Partial correlations with MSA demographics, however, are more robust. Incorporating the past concentration lag explains 88% of the MSA-level variation in inventor shares (83% by itself).¹¹

The subsequent eight columns of Table 3 consider major non-English inventor shares. The estimation framework remains the same excepting the 1975-1984 MSA inventor shares in the even-numbered columns that are adjusted to match the dependent variable. Most explanatory variables (e.g., MSA demographics) demonstrate similar elasticities across ethnic groups. Coastal access tends to be more important, although of borderline statistical significance. This reflects the well-known tendency for immigrants to locate in port cities closer to their home countries.

Several interesting differences, however, emerge. First, the overall explanatory power of these regressors varies across ethnic groups. The R^2 values for the Chinese and Indian ethnicities are substantially lower than those for the European and Hispanic ethnicities. These Asian ethnicities thus have more idiosyncratic spatial patterns than this limited set of covariates modelled. This is confirmed when the even-numbered columns incorporate the lagged ethnic inventor shares. The gain in the variation explained through past MSA-specific placements is strongest for Chinese and Indian inventors. This strength suggests that lagged spatial patterns for Asian inventors may offer an empirical foothold for predicting future MSA-level innovation even conditional on other MSA-level traits.

¹¹Unreported specifications further incorporate mean wages in manufacturing, mean family income levels, and mean housing prices by MSA. Positive correlations between inventor shares and manufacturing wages are generally found; family income levels and housing prices do not exhibit robust relationships in multi-variate settings. The inclusion of these three covariates has very limited influence on the reported outcomes.

These even-numbered columns also show that lagged ethnic inventor shares tend to have weaker predictive power for subsequent MSA-level concentration compared to the English ethnicity in Column 2. The elasticities range from 0.87 for Chinese patents to 0.53 for Hispanic patents (which is lowest among the nine ethnic inventor groups). This lower explanatory power has at least two explanations. First, spatial distributions for ethnic inventors over 1975-1984 may have greater measurement error than English inventor distributions due to smaller counts of relevant patents. Such measurement error would downward bias estimated elasticities.

Nonetheless, it is also true that ethnic inventors facilitate shifts in invention locations across US MSAs. For example, immigrant SE students graduating from elite US universities enter a national labor market. Hispanic inventors have supported broader growth in Florida and the southwestern states. While past immigration cities are favored, ethnic inventors also have an inherent capacity to facilitate regional adjustments. Unreported estimations further test this conclusion by controlling simultaneously for each MSA's 1975-1984 English inventor share and ethnic-specific inventor share. With the exception of the European and Russian ethnicities, lagged ethnic spatial distributions have stronger predictive power for subsequent agglomeration than lagged English spatial distributions.

Table 4 repeats the estimations without the MSA population weights. The measured partial correlations decline in magnitude somewhat, reflective of the greater attention paid to smaller MSA shares, but the patterns of coefficients and explanatory power are comparable to the weighted outcomes. Several additional specification checks are also undertaken. Incorporating regional fixed effects finds anticipated spatial patterns — Midwestern US MSAs tend to have higher invention rates conditional on the covariates modelled, while southern MSAs have lower rates. The east and west coasts are often not statistically distinguishable from each other conditionally. Performing the share estimations on an annual basis, which circumvents growth in recent patent application rates, yields similar outcomes to the cross-sectional results. Likewise, log specifications produce outcomes similar to the share specification framework.

Of course, these estimations must be interpreted as partial correlations rather than causal assessments. Clearly, ethnic inventors directly influence many of the determinants modelled (e.g., education shares) and may also have local spillover effects through their work (e.g., local technology gains that generate city population growth). Future work hopes to further refine these determinants in a causal assessment.

Ongoing research is further evaluating how shifts in the geographic concentration of ethnic inventors facilitate changes in the geographic composition of US innovation. Not only are ethnic scientists disproportionately concentrated in major MSAs, but growth in a MSA's share of ethnic patenting is highly correlated with growth in its share of total US patenting. Annual regressions across the full 1975-2004 MSA sample find that an increase of 1% in an MSA's ethnic patenting

share correlates with a 0.6% increase in the MSA’s total invention share. This coefficient is remarkably high, as the mean ethnic share of total invention during this period is around 20%. Of course, additional study is required before causal assessments are possible. The ethnic-name approach will also need to be complemented with external data to distinguish ethnic inventor shifts due to new immigration, domestic migration, or occupational changes.

3.3 Spatial Concentration of US Ethnic Inventors

To refine the earlier visual observations made regarding agglomeration levels in Table 2, Table 5 presents three concentration indices for US domestic patenting. The first concentration metric studied is the Herfindahl-Hirschman Index defined by $HHI_t = \sum_{m=1}^M Share_{mt}^2$, where M indexes 283 MSAs and $Share_{mt}$ is the share of patenting in MSA m in period t . Of course, patenting is undertaken outside of MSAs, too. The share of patenting outside of these 283 MSAs declines from 9% in 1975-1984 to 7% in 1995-2004. In 2001-2006 applications, this share further declines to 5%. This portion of US invention is excluded from the remainder of this paper, with concentration metrics being calculated over MSA patenting only.

The top panel of Table 5 and Figure 2 highlight several important levels differences. First, US invention is more concentrated than the general population across these MSAs.¹² Moreover, ethnic inventors are substantially more agglomerated than English-ethnicity inventors throughout the thirty years considered. The mean population HHI is 0.024 over the period, compared with 0.037 for invention and 0.059 for all non-English inventors. The agglomeration of Chinese inventors further stands out at 0.081. This higher ethnic concentration certainly reflects the well-known concentration of immigrant groups, but is not due to simply the smaller sizes of some ethnicities. Chinese, Japanese, and Vietnamese are consistently the most agglomerated of ethnic inventor groups. European and Hispanic inventors are the least concentrated, but all ethnic groups are more agglomerated than the English ethnicity.¹³

Moving from the levels to the trends evident in Table 5 and Figure 2, the HHI for all US inventors consistently declines from 1975-1979 to 1990-1994. This trend is reversed, however, with greater levels of invention agglomeration in 1995-1999 and 2000-2004. This reversal towards greater patenting concentration is not reflected in the overall population shares. Ethnic inventors, however, show a sharp increase in these latter ten years. This upturn is strongest among Asian ethnic groups, with European and Hispanic inventors showing limited change in agglomeration.

¹²MSA populations are calculated through county populations collected in 1977, 1982, 1987, 1992, and 1997. These are mid-points of the five-year increments studied. The 2000-2004 period uses the 1997 MSA population.

¹³Calculations from the 1990 and 2000 Census of Populations find that the aggregate concentration of immigrant SEs is slightly less than the agglomeration of all immigrants. Substantial differences in immigrant shares are evident in larger cities. New York City, Los Angeles, and Miami have larger overall immigration pools relative to SE, while San Francisco, Washington, Boston, and Seattle have greater SE shares.

A second agglomeration metric is calculated as the share of total US patenting in the Top 5 MSAs for 1975-1984: New York City (12%), Los Angeles (7%), Chicago (6%), Philadelphia (5%), and San Francisco (5%). Boston (4%) and Detroit (3%) have the next two largest shares in 1975-1984. These five MSAs account for about 37% of MSA patenting during this initial period and 34% of total US patenting that includes rural areas. The share accounted for by these five MSAs behaves similarly to the *HHI* metric, declining until 1990-1994 before growing during 1995-2004. While less formal, this second technique highlights how ethnic agglomeration shifts across the major US MSAs. By 1995-2004, San Francisco (12%) leads New York City (7%) and Los Angeles (6%). Boston and Chicago would complete a new Top 5 MSAs list for 1995-2004.

Our final agglomeration metric is taken from Ellison and Glaeser (1997),

$$\gamma_e^{Agg} = \frac{\sum_{m=1}^M (s_{m,e} - x_m)^2}{1 - \sum_{m=1}^M x_m^2},$$

where M indexes MSAs. $s_{1,e}, s_{2,e}, \dots, s_{M,e}$ are the shares of ethnicity e 's patenting contained in each of these geographic areas. x_1, x_2, \dots, x_M are each area's share of population.¹⁴ This metric estimates the agglomeration of invention relative to the baseline established by the MSA populations. If invention is randomly distributed among the population, the Ellison and Glaeser metric will not show concentration. The bottom panel of Table 5 and Figure 3 report these indices. When judged relative to the overall population's distribution, the trends in the agglomeration of invention look a little different. The 1975-1994 periods are found to have fairly consistent levels of concentration, with a strong upturn in the 1995-2004 years. This pattern is predicted by the growing deviations with time in the *HHI* trends in Panel A.

Following Ellison et al. (2007), the pairwise coagglomeration of invention between ethnicity e_1 and e_2 is analyzed with the simple formula

$$\gamma_{e_1, e_2}^{Coagg} = \frac{\sum_{m=1}^M (s_{m, e_1} - x_m)(s_{m, e_2} - x_m)}{1 - \sum_{m=1}^M x_m^2}.$$

This index measures the covariance of ethnic invention across MSAs, with the denominator rescaling the covariance to eliminate a sensitivity to the fineness of the geographic breakdown. The coagglomeration indices are contained in the appendix. Coagglomeration among non-English ethnic inventors is substantially higher than between English inventors and these groups. This is especially true among the Asian ethnicities. These coagglomeration measures rise in recent years, behaving similarly to the agglomeration measures when relative to the total population.

¹⁴The full Ellison and Glaeser (1997) formula also controls for the HHI index of plant size. This feature is ignored in this examination of individual inventors. The ethnic patenting data do not easily support continuous estimators like Duranton and Overman (2005), although future research hopes to approximate these metrics too.

3.4 Technology Concentration of US Ethnic Inventors

Figure 4 documents the total ethnic contribution by the six broad technology groups into which patents are often classified: Chemicals, Computers and Communications, Drugs and Medical, Electrical and Electronic, Mechanical, and Miscellaneous/Others. The Miscellaneous group includes patents for agriculture, textiles, furniture, and the like. Growth in ethnic patenting is noticeably stronger in high-tech sectors than in more traditional industries. Figures 5 and 6 provide more detailed glimpses within the Chinese and Indian ethnicities, respectively. These two ethnic groups are clearly important contributors to the stronger growth in ethnic contributions among high-tech sectors, where Chinese inventors supplant European researchers as the largest ethnic contributor to US technology formation.¹⁵

One possible explanation for Table 5's aggregate gains in concentration is compositional shifts in the volume and nature of granted patents, rather than a shift in underlying innovation per se. There has been a substantial increase in the number of patents granted by the USPTO over the last two decades. While this increase is partly due to population growth and higher levels of US innovation, institutional factors also play an important role.¹⁶ The heightened agglomeration may be driven by greater patenting rates by certain technology groups, reflecting either true changes in the underlying innovation rates or simply a greater propensity to seek patent protection. The latter is especially relevant for the recent rise of software patents (e.g., Graham and Mowery 2004). Microsoft and other software companies are among the US's largest firms today in terms of patent applications, but historically this industry did not seek patent protection.

Table 6 considers the geographic concentration of invention that exists within each of the six broad technology groupings. Panel A presents *HHI* measures calculated over all patents within each technology. The exceptional rebounds for 1995-2004 are strongest within the Computers and Communications and Electrical and Electronic groupings. Drugs and Medical and Mechanical categories also demonstrate weaker gains, while Chemicals and Miscellaneous show steady trends for less spatial agglomeration throughout the 1975-2004 period.

The dual responses within the Computers and Communications and Electrical and Electronic groupings suggest that the greater agglomeration is more of a high-tech phenomena than software in particular. This conclusion is further confirmed in the appendix. In these estimations, agglomeration is calculated for each sub-category within the six broad technology divisions;

¹⁵The USPTO issues patents by technology categories rather than by industries. Combining the work of Johnson (1999), Silverman (1999), and Kerr (2008), concordances can be developed to map the USPTO classification scheme to the three-digit industries in which new inventions are manufactured or used. Scherer (1984) and Keller (2002) further discuss the importance of inter-industry R&D flows.

¹⁶For example, Griliches (1990), Kortum and Lerner (2000), Kim and Marschke (2004), Hall (2005), Jaffe and Lerner (2005).

there are four to nine sub-categories within each division. In both weighted and unweighted estimations, the concentration metrics at the sub-category level behave similarly to Table 6. This robustness highlights that a few isolated technology categories, either pre-existing or entering with recent USPTO additions, are not solely responsible for the patterns evident.

Panels B and C report similar indices for English and non-English ethnicity inventors. Some of the sharp concentration gains within the Computers and Communications and Electrical and Electronic groupings can be traced to higher agglomeration of the English inventors. The exceptional growth in concentration among non-English ethnic inventors, however, is even more striking. Figure 7 presents the *HHI* of Computers and Communications patents for selected ethnic groups. The Chinese *HHI* reaches just less than 0.200 by 2000-2004, while the Indian concentration also grows to 0.141. Note that this concentration growth occurs during a period of growing patent counts.

Ethnic inventors thus pull up the overall patenting concentration in at least two ways. First, ethnic inventors have higher levels of existing concentration and are becoming a larger share of US patenting (Figure 4). Even if their own concentration holds constant, this should lead to an increase in the agglomeration of US patenting. Second, ethnic inventors are themselves becoming more spatially concentrated in high-tech fields. This force also leads to an increase in overall agglomeration levels. (Ethnic inventors are also more concentrated in fields that have experienced greater rates of recent patenting, yielding a mechanical link as well.)¹⁷

3.5 Institutional Concentration of US Ethnic Inventors

Patents are granted to several types of institutions. Industrial firms account for about 70% of patents granted from 1980-1997, while government and university institutions are assigned about 4% of patents. Unassigned patents (e.g., individual inventors) represent about 26% of US invention. Public companies account for 59% of the industry patents during this period. With the exception of unassigned patents, institutions are primarily identified through assignee names on patents.

Figure 8 demonstrates that intriguing differences in ethnic scientific contributions also exist by institution type. Over the 1975-2004 period, ethnic inventors are more concentrated in government and university research labs and in publicly-listed companies than in private companies or as unaffiliated inventors. Part of this levels difference is certainly due to immigration visa

¹⁷These effects appear to continue in the 2001-2006 applications data catalogued in Table 2, where San Francisco's patenting share further climbs to 15% from its 12% share in 1995-2004 granted patents. Seattle (6%) and Boston (5%) also demonstrate exceptional increases. Ongoing work seeks to separate the factors leading to geographic differences between the granted patents data and the newer applications data.

sponsorships by larger institutions. Growth in ethnic shares are initially stronger in the government and university labs, but publicly-listed companies appear to close the gap by 2004. The other interesting trend in Figure 8 is for private companies, where the ethnic contribution sharply increases in the 1990s. This rise coincides with the strong growth in ethnic entrepreneurship in high-tech sectors.¹⁸

Panels A and B of Table 7 document the evolution of the *HHI* concentration for industry and university/government patenting, respectively. The column headers again indicate different technology groups. Despite having fairly similar levels of spatial concentration, the differences between institutions in the agglomeration trends for patenting are striking. The concentration of invention within universities and governments has either weakened or remained constant in every technology group. The recent gains in industry concentration, on the other hand, are stronger than the aggregate statistics from Table 6. Whereas the recent growth in industry concentration is strongest for Computers and Communications and Electrical and Electronic, the two technology groups show above-average declines for universities and government bodies.

The bottom two panels of Table 7 show the deeper impact of these institutional differences for non-English invention. Ethnic inventors are again very strong drivers for the recent agglomeration increases in industry patenting within high-tech sectors. On the other hand, ethnic inventors are not becoming more geographically agglomerated within universities and government institutions. This even holds true for Chinese and Indian groups within the Computers and Communications and Electrical and Electronic technology sectors. Figures 9 and 10 summarize these differences. As universities and government bodies are more constrained from agglomerating than industrial firms, these differences provide a nice falsification check on the earlier trends and the role of ethnic inventors.¹⁹

4 Conclusions

Ethnic scientists and engineers are an important and growing contributor to US technology development. The Chinese and Indian ethnicities, in particular, are now an integral part of US invention in high-tech sectors. The magnitude of these ethnic contributions raises many research and policy questions: debates regarding the appropriate quota for H-1B temporary visas, the possible crowding out of native students from SE fields, the brain drain or brain circulation

¹⁸Publicly-listed companies are identified from a 1989 mapping developed by Hall et al. (2001). This company list is not updated for delistings or new public offerings. This approach maintains a constant public grouping for reference, but it also weakens the representativeness of the public and private company groupings at the sample extremes for current companies.

¹⁹Trends in concentration ratios of unassigned inventors fall in between industry and university/government, behaving more closely like the latter. While there is some recent growth in ethnic inventor concentration within this class, the upturn is much weaker than in industrial firms. Figure 8 also highlights that ethnic inventors are a smaller fraction of unassigned patents, leading to much less impact on aggregate statistics.

effect on sending countries, and the future prospects for US technology leadership are just four examples.²⁰ While the answers to these questions must draw from many fields within and outside of economics, valuable insights can be developed through agglomeration theory and empirical studies.

This paper builds a new empirical platform for these research questions by assigning probable ethnicities for US inventors through the inventor names available with USPTO patent records. The resulting data document with greater detail than previously available the powerful growth in US Chinese and Indian inventors during the 1990s. At the same time, these ethnic inventors became more spatially concentrated across US cities. The combination of these two factors helps stop and reverse long-term declines in overall inventor agglomeration evident in the 1970s and 1980s. The heightened ethnic agglomeration is particularly evident in industry patents for high-tech sectors, and similar trends are not found in institutions constrained from agglomerating (e.g., universities, government).

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²⁰Representative papers are Lowell (2000), Borjas (2005), Saxenian (2002b), and Freeman (2005), respectively.

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Fig. 1: Ethnic Share of US Domestic Patents

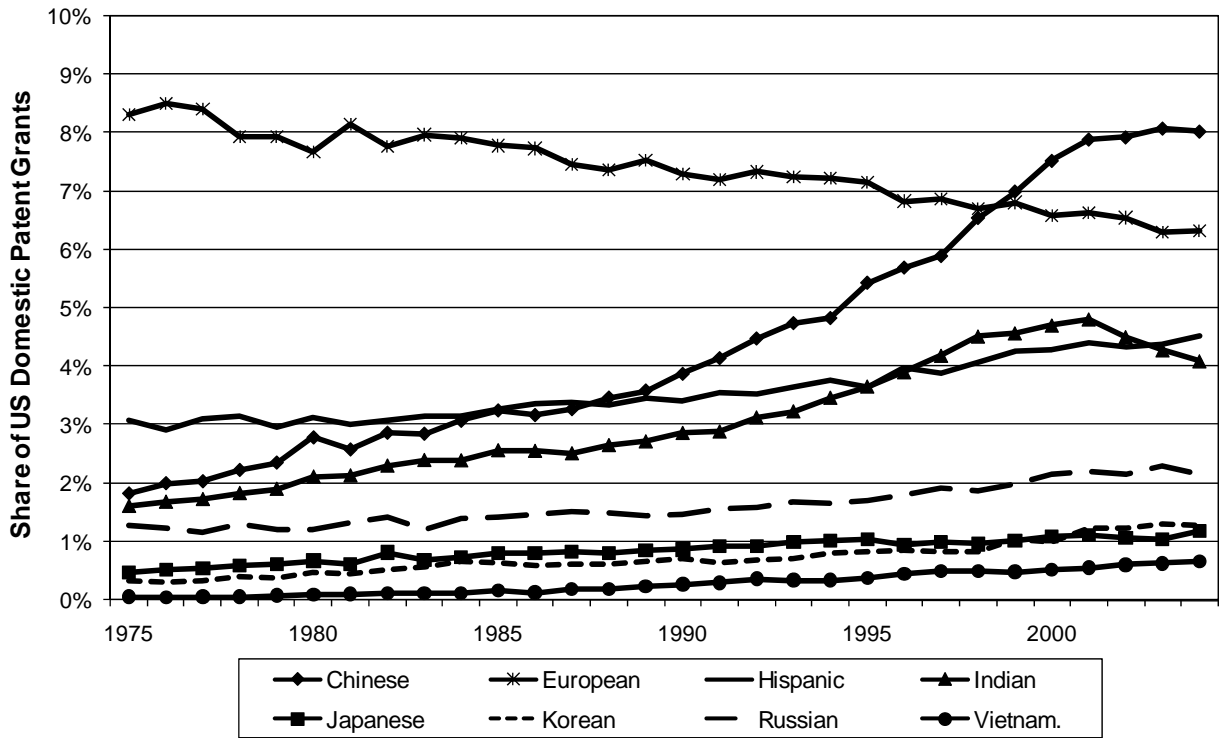


Fig. 2: HHI Concentration of US Patents

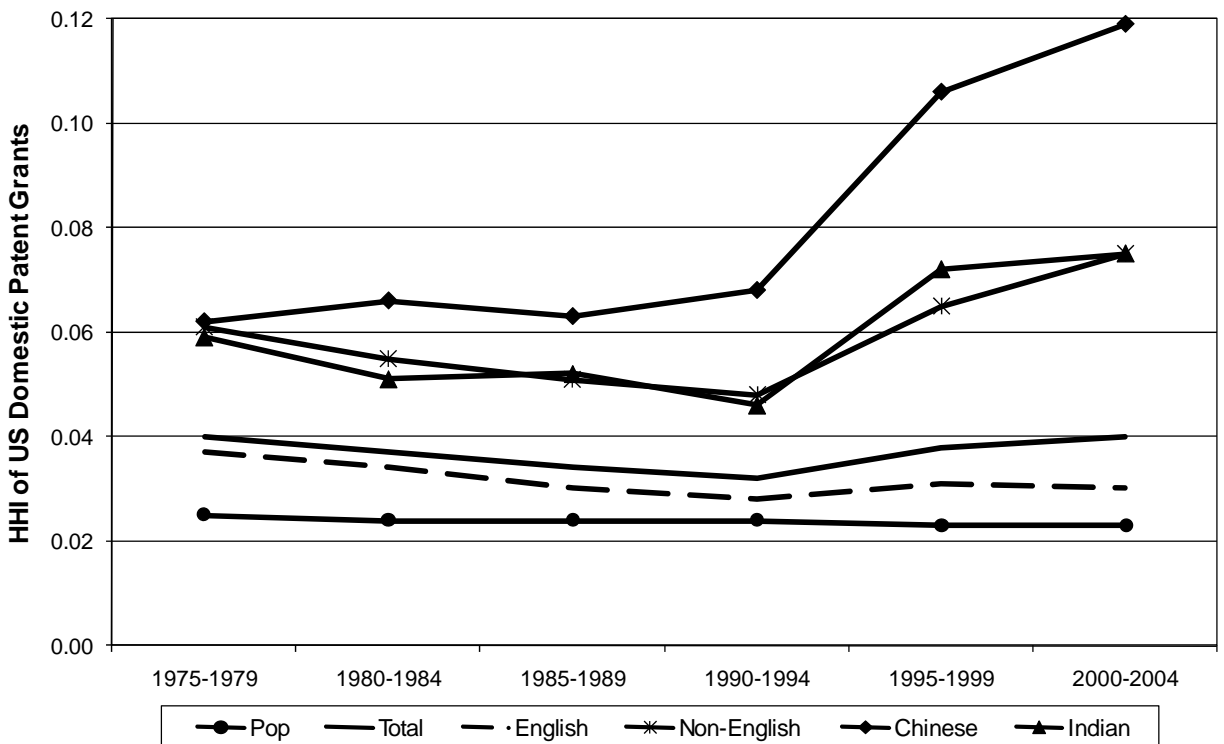


Fig. 3: EG Concentration of US Patents

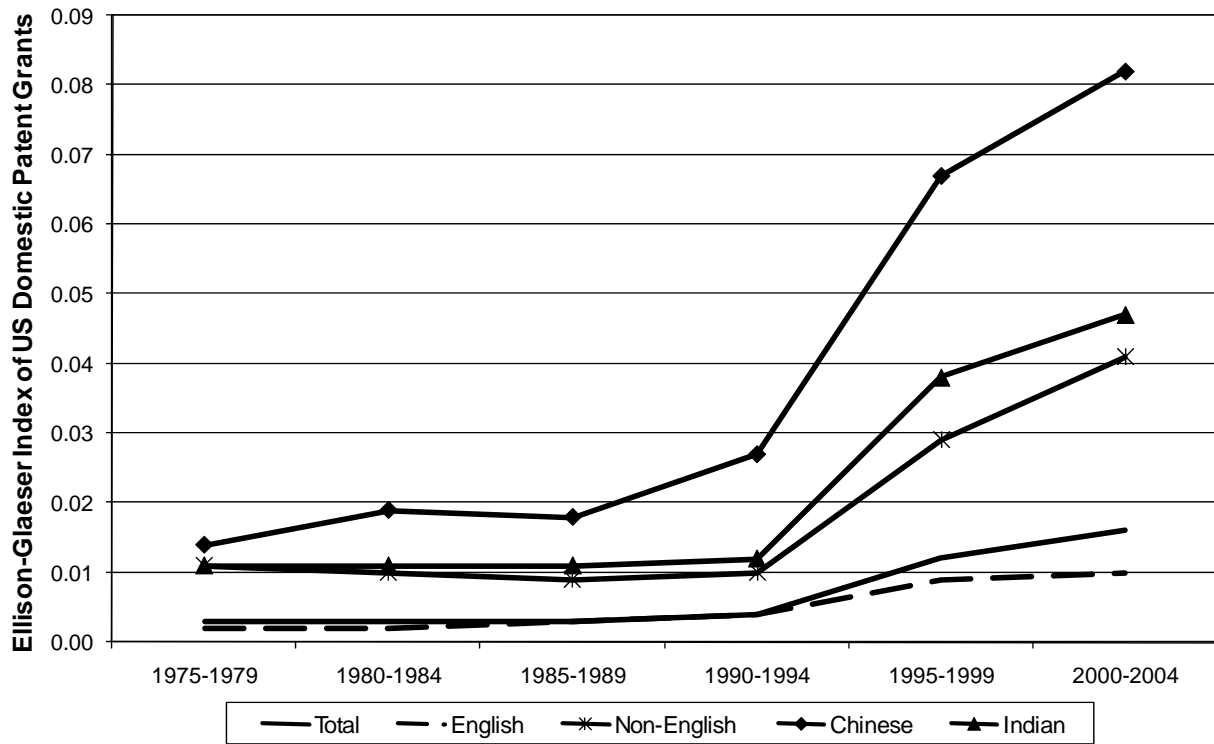


Fig. 4: Total US Ethnic Share by Technology

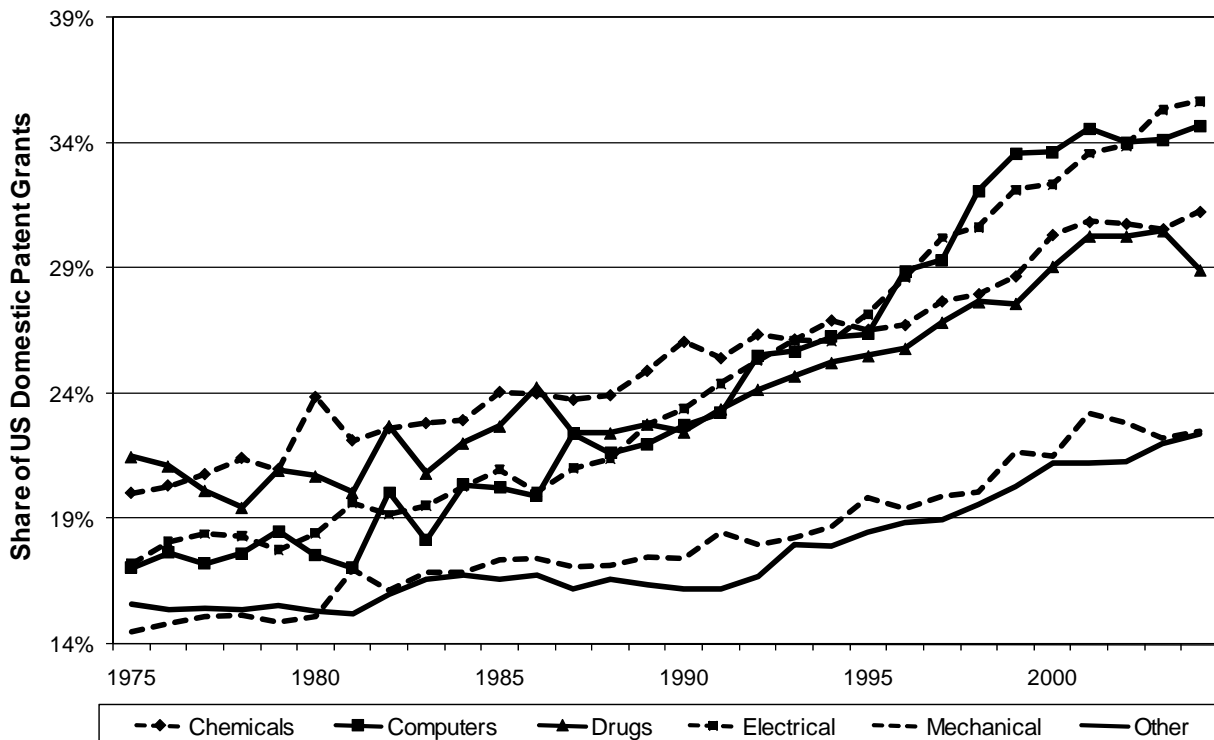


Fig. 5: Chinese Contribution by Technology

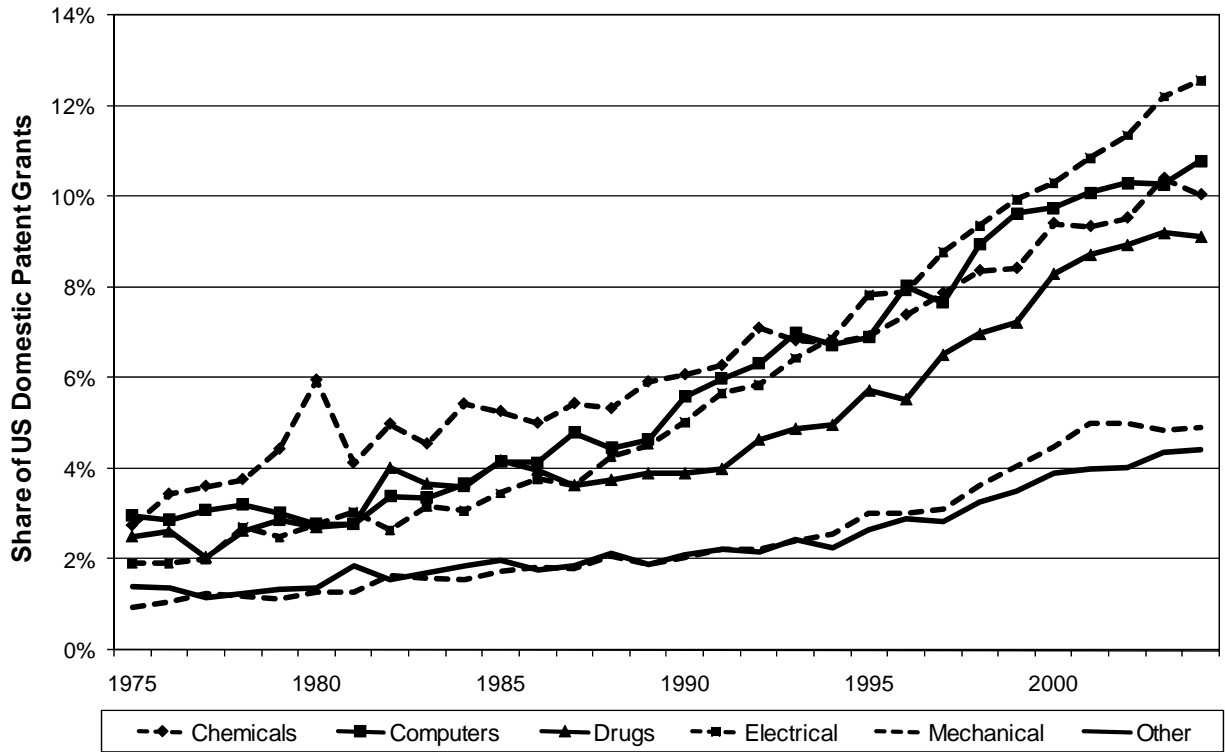


Fig. 6: Indian Contribution by Technology

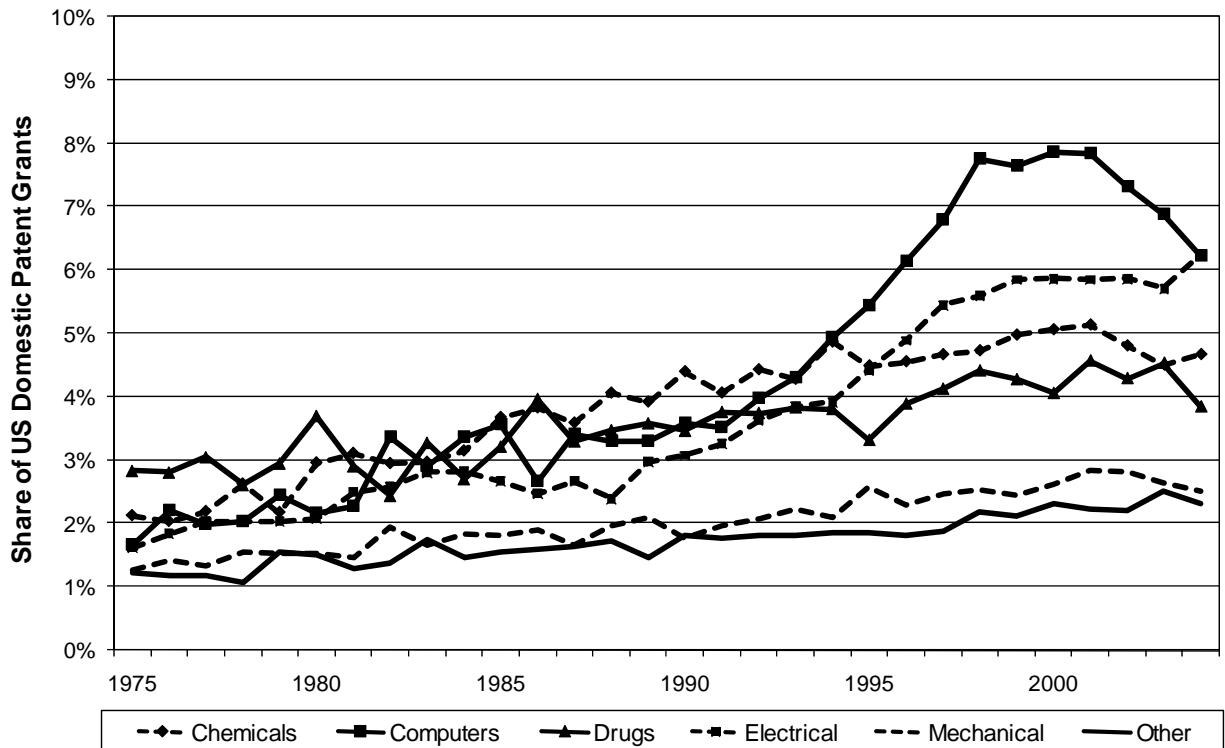


Fig. 7: Ethnic Concentration in Computers

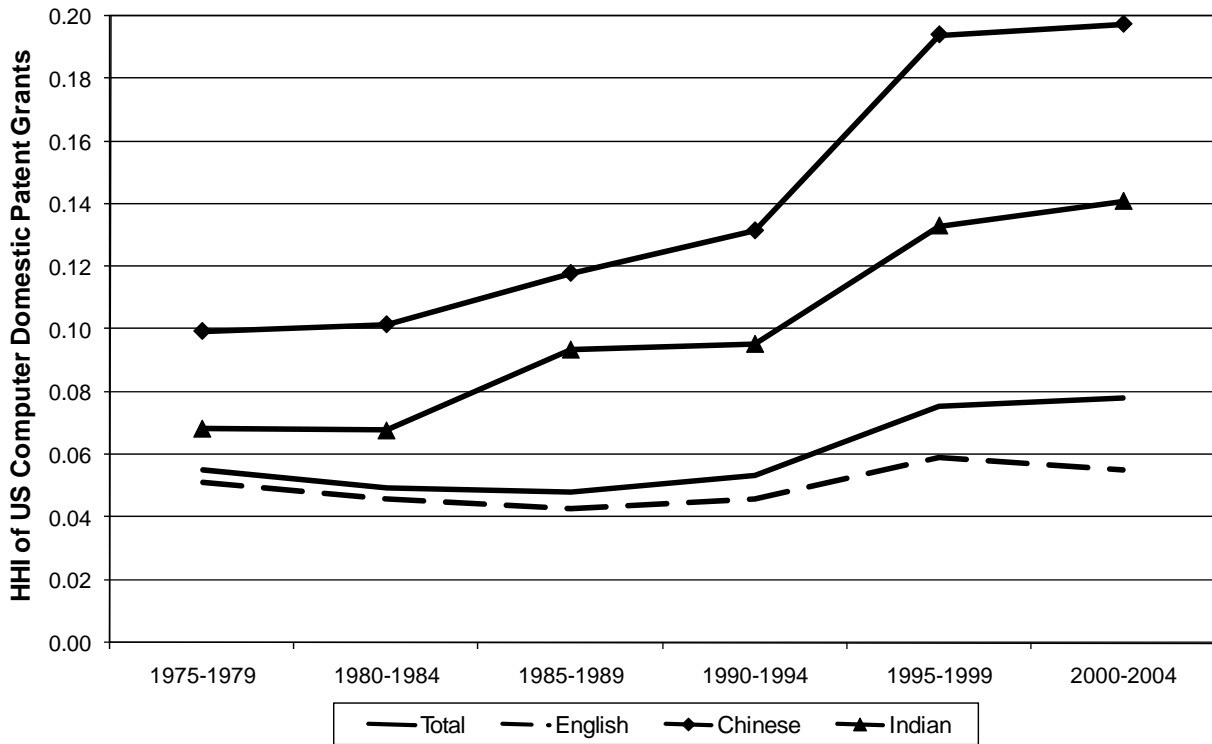


Fig. 8: Total US Ethnic Share by Institution

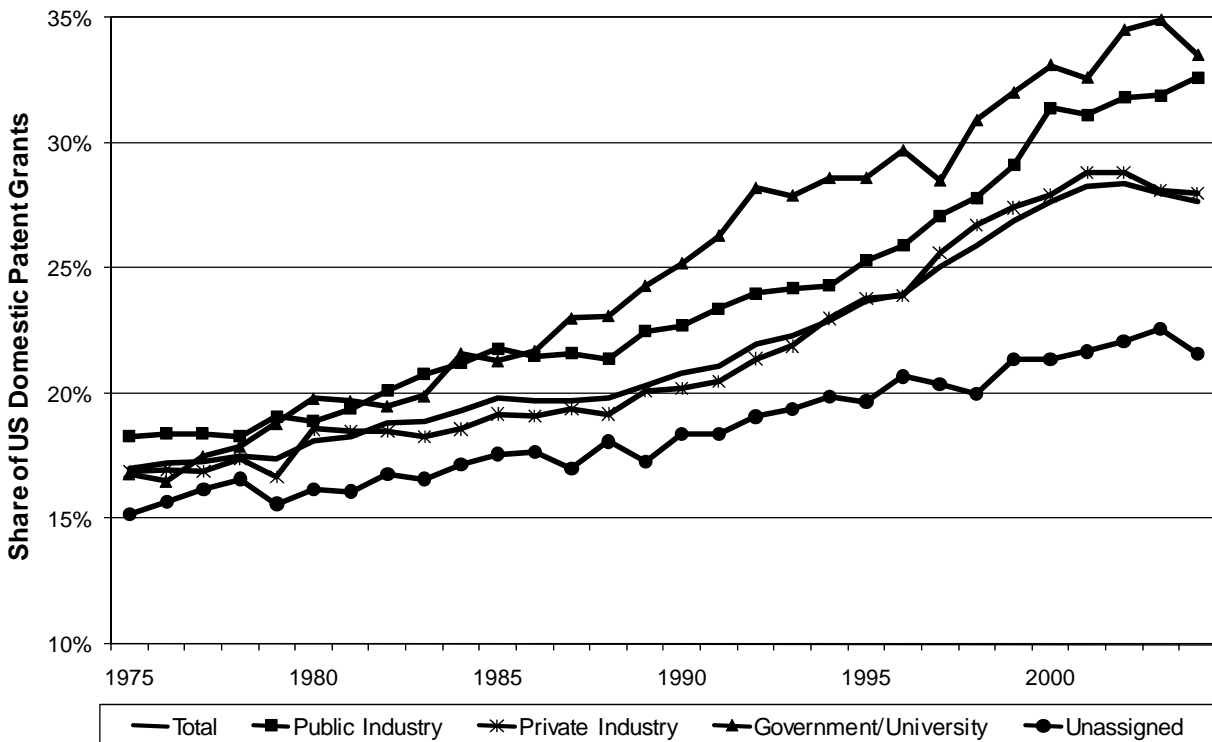


Fig. 9: Ethnic HHI, All Inventors

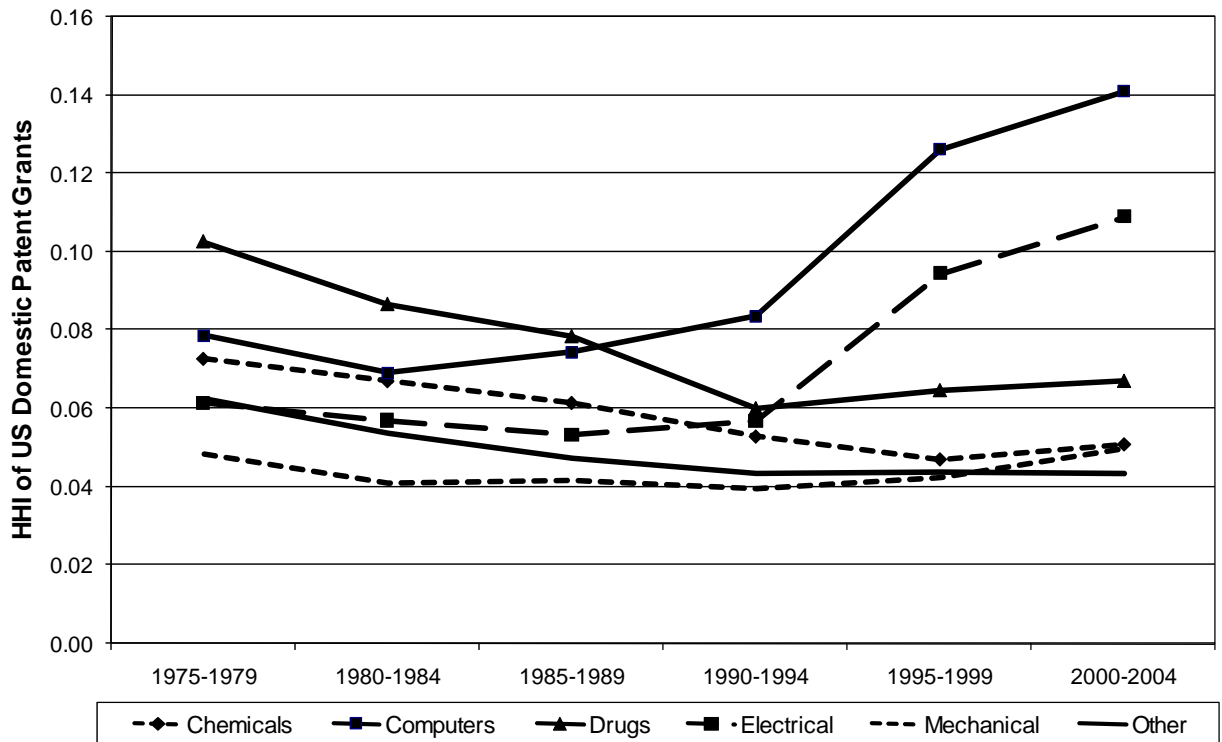


Fig. 10: Ethnic HHI, University & Government

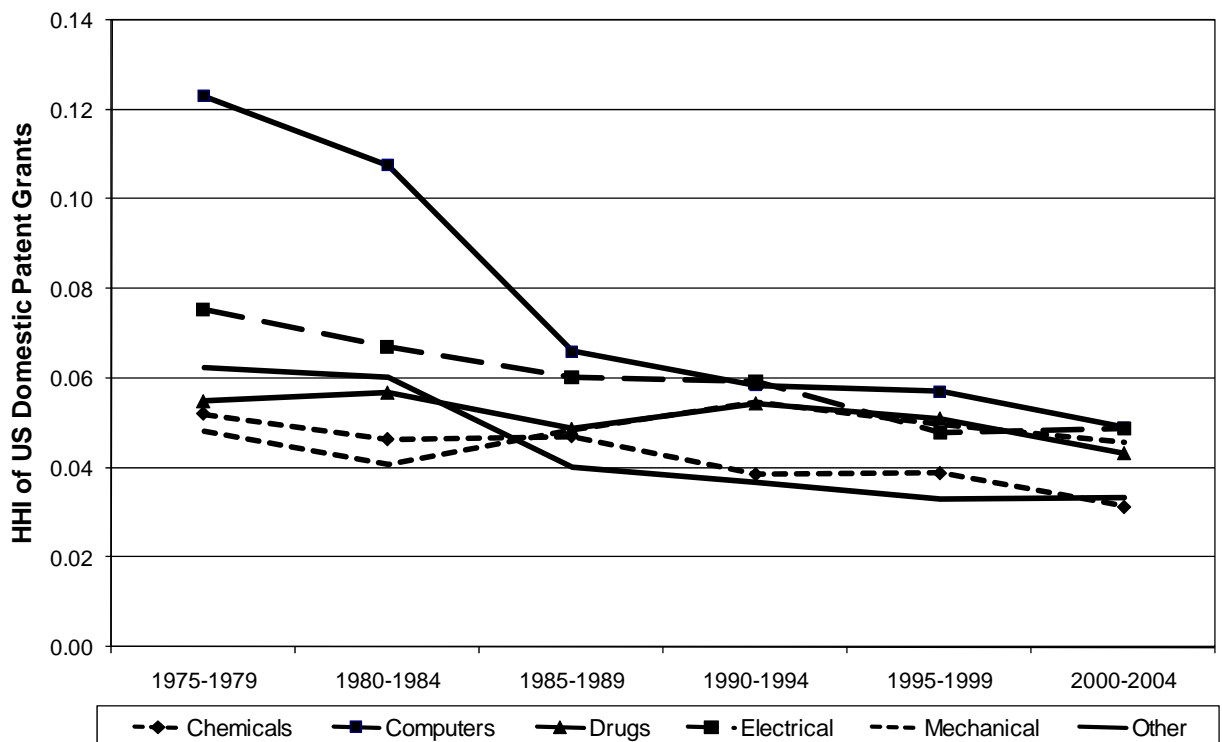


Table 1: Descriptive Statistics for Inventors Residing in US

	Ethnicity of Inventor								
	English	Chinese	European	Hispanic	Indian	Japanese	Korean	Russian	Vietnam.
A. Ethnic Inventor Shares Estimated from US Inventor Records									
1975-1979	82.5%	2.2%	8.2%	3.0%	1.9%	0.6%	0.4%	1.2%	0.1%
1980-1984	81.1%	2.9%	7.9%	3.1%	2.4%	0.7%	0.6%	1.3%	0.1%
1985-1989	79.8%	3.6%	7.5%	3.3%	2.8%	0.8%	0.7%	1.4%	0.2%
1990-1994	77.6%	4.7%	7.2%	3.5%	3.4%	0.9%	0.8%	1.5%	0.4%
1995-1999	74.0%	6.6%	6.8%	3.9%	4.5%	0.9%	0.9%	1.8%	0.5%
2000-2004	71.0%	8.5%	6.4%	4.2%	4.8%	1.0%	1.2%	2.2%	0.6%
Chemicals	73.7%	7.1%	7.6%	3.6%	4.2%	0.9%	0.9%	1.7%	0.3%
Computers	71.3%	7.9%	6.3%	3.7%	6.1%	1.1%	1.0%	2.0%	0.7%
Pharmaceuticals	73.3%	6.9%	7.4%	4.3%	3.9%	1.1%	1.0%	1.8%	0.3%
Electrical	72.0%	8.0%	6.8%	3.7%	4.6%	1.1%	1.2%	2.0%	0.7%
Mechanical	80.6%	3.2%	7.2%	3.4%	2.4%	0.7%	0.6%	1.6%	0.2%
Miscellaneous	81.5%	2.9%	7.0%	3.8%	2.1%	0.6%	0.6%	1.4%	0.2%
Top MSAs as a Percentage of MSA's Patents	KC (89) WS (88) NAS (88)	SF (14) LA (8) AUS (6)	NOR (12) STL (11) NYC (11)	MIA (16) SA (9) WPB (7)	AUS (6) SF (6) BUF (5)	SF (2) SD (2) LA (2)	BAL (2) LA (2) SF (2)	BOS (3) NYC (3) SF (3)	AUS (2) SF (1) PRT (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: MSAs - AUS (Austin), BAL (Baltimore), BOS (Boston), BUF (Buffalo), 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). MSAs 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. 1990 Census statistics are calculated by country-of-birth using the groupings listed in the appendix; English provides a residual in the Census statistics.

Table 2: Ethnic Inventor Contributions by MSA

	Total Patenting Share				Ethnic Patenting Share				Chinese Patenting Share			
	1975-1984	1985-1994	1995-2004	2001-2006 (A)	1975-1984	1985-1994	1995-2004	2001-2006 (A)	1975-1984	1985-1994	1995-2004	2001-2006 (A)
Atlanta, GA	0.6%	1.0%	1.3%	1.3%	0.3%	0.7%	1.0%	1.0%	0.3%	0.6%	0.8%	0.8%
Austin, TX	0.4%	0.9%	1.8%	2.8%	0.5%	1.2%	1.9%	2.8%	0.5%	1.6%	1.7%	2.2%
Baltimore, MD	0.8%	0.8%	0.7%	0.6%	0.7%	0.7%	0.7%	0.5%	0.4%	0.5%	0.6%	0.5%
Boston, MA	3.6%	3.8%	3.9%	5.1%	3.9%	4.2%	4.1%	5.1%	3.5%	4.1%	3.5%	4.6%
Buffalo, NY	0.6%	0.5%	0.4%	0.2%	0.8%	0.6%	0.4%	0.2%	0.9%	0.5%	0.3%	0.1%
Charlotte, NC	0.3%	0.3%	0.3%	0.3%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.2%
Chicago, IL	6.0%	4.6%	3.5%	2.7%	6.9%	5.1%	3.5%	2.4%	5.0%	3.9%	2.9%	2.0%
Cincinnati, OH	1.0%	1.1%	1.0%	1.2%	0.9%	0.9%	0.7%	0.9%	0.8%	0.8%	0.6%	0.7%
Cleveland, OH	2.3%	1.7%	1.4%	1.1%	2.5%	1.5%	1.0%	0.8%	2.0%	1.2%	0.8%	0.6%
Columbus, OH	0.7%	0.5%	0.5%	0.3%	0.6%	0.6%	0.4%	0.2%	0.6%	0.4%	0.3%	0.2%
Dallas-Fort Worth, TX	1.6%	2.0%	2.2%	2.1%	1.1%	1.9%	2.3%	2.4%	1.4%	2.4%	2.5%	2.5%
Denver, CO	1.1%	1.2%	1.3%	1.4%	0.8%	1.0%	0.9%	0.8%	0.9%	1.2%	0.5%	0.4%
Detroit, MI	3.1%	3.3%	3.0%	2.5%	3.1%	3.1%	2.7%	2.3%	2.4%	1.9%	2.4%	2.0%
Greensboro-W.S., NC	0.2%	0.3%	0.3%	0.2%	0.1%	0.2%	0.2%	0.1%	0.2%	0.2%	0.1%	0.1%
Hartford, CT	0.9%	0.9%	0.6%	0.5%	0.9%	0.8%	0.5%	0.4%	0.5%	0.5%	0.3%	0.2%
Houston, TX	2.3%	2.5%	1.9%	1.8%	1.8%	2.3%	1.8%	1.8%	2.0%	3.2%	1.7%	1.7%
Indianapolis, IN	0.8%	0.7%	0.7%	0.3%	0.6%	0.5%	0.4%	0.2%	0.6%	0.4%	0.4%	0.2%
Jacksonville, NC	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.1%	0.1%	0.1%	0.0%
Kansas City, MO	0.4%	0.3%	0.4%	0.3%	0.2%	0.2%	0.2%	0.1%	0.2%	0.1%	0.1%	0.1%
Las Vegas, NV	0.1%	0.1%	0.2%	0.2%	0.1%	0.1%	0.2%	0.1%	0.0%	0.0%	0.1%	0.0%
Los Angeles, CA	6.6%	6.1%	6.1%	4.6%	7.1%	7.2%	8.2%	6.0%	7.4%	8.7%	10.0%	7.4%
Memphis, TN	0.1%	0.2%	0.2%	0.3%	0.1%	0.1%	0.1%	0.2%	0.1%	0.1%	0.1%	0.1%
Miami, FL	0.8%	0.9%	0.7%	0.5%	1.0%	1.3%	1.0%	0.6%	0.4%	0.5%	0.3%	0.3%
Milwaukee, WI	1.0%	0.9%	0.8%	0.6%	0.8%	0.8%	0.6%	0.4%	0.4%	0.4%	0.5%	0.3%
Minneapolis-St. Paul, MN	1.9%	2.4%	2.6%	3.8%	1.6%	2.0%	1.9%	2.5%	1.5%	1.6%	1.8%	2.5%

Table 2: Ethnic Inventor Contributions by MSA, continued

	Total Patenting Share				Ethnic Patenting Share				Chinese Patenting Share			
	1975- 1984	1985- 1994	1995- 2004	2001- 2006 (A)	1975- 1984	1985- 1994	1995- 2004	2001- 2006 (A)	1975- 1984	1985- 1994	1995- 2004	2001- 2006 (A)
Nashville, TN	0.1%	0.2%	0.2%	0.2%	0.0%	0.1%	0.1%	0.1%	0.0%	0.1%	0.1%	0.1%
New Orleans, LA	0.3%	0.2%	0.2%	0.1%	0.3%	0.3%	0.1%	0.0%	0.2%	0.2%	0.0%	0.0%
New York, NY	11.5%	8.9%	7.2%	6.5%	16.6%	13.1%	9.9%	8.7%	16.6%	12.5%	8.8%	8.4%
Norfolk-VA Beach, VA	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%
Orlando, FL	0.2%	0.3%	0.3%	0.3%	0.1%	0.2%	0.3%	0.3%	0.1%	0.1%	0.3%	0.2%
Philadelphia, PA	4.6%	3.9%	2.7%	2.1%	5.7%	4.9%	2.8%	1.9%	7.2%	6.1%	2.9%	2.0%
Phoenix, AZ	1.0%	1.2%	1.4%	1.1%	0.6%	1.1%	1.3%	1.0%	0.4%	0.9%	1.3%	0.7%
Pittsburgh, PA	2.0%	1.3%	0.8%	0.6%	2.2%	1.4%	0.6%	0.5%	2.1%	1.0%	0.5%	0.4%
Portland, OR	0.5%	0.8%	1.4%	1.2%	0.3%	0.6%	1.3%	1.2%	0.1%	0.6%	1.4%	1.2%
Providence, RI	0.3%	0.3%	0.3%	0.2%	0.3%	0.4%	0.3%	0.3%	0.1%	0.3%	0.2%	0.3%
Raleigh-Durham, NC	0.3%	0.6%	1.1%	1.8%	0.3%	0.6%	1.0%	1.4%	0.3%	0.6%	0.8%	1.1%
Richmond, VA	0.3%	0.3%	0.2%	0.2%	0.3%	0.3%	0.2%	0.2%	0.5%	0.4%	0.2%	0.2%
Sacramento, CA	0.2%	0.4%	0.5%	0.3%	0.2%	0.4%	0.5%	0.3%	0.2%	0.3%	0.4%	0.3%
Salt Lake City, UT	0.4%	0.5%	0.6%	0.4%	0.2%	0.4%	0.3%	0.3%	0.2%	0.3%	0.3%	0.2%
San Antonio, TX	0.1%	0.2%	0.2%	0.3%	0.1%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%
San Diego, CA	1.1%	1.6%	2.1%	2.4%	1.1%	1.6%	2.5%	2.9%	1.1%	1.5%	2.4%	3.1%
San Francisco, CA	4.8%	6.6%	11.8%	15.2%	6.2%	9.4%	19.1%	22.3%	10.1%	15.9%	28.1%	29.0%
Seattle, WA	0.9%	1.3%	1.8%	5.7%	0.8%	1.1%	1.7%	6.1%	0.6%	1.0%	1.6%	5.2%
St. Louis, MO	1.0%	0.9%	0.8%	0.7%	0.9%	0.8%	0.7%	0.5%	1.2%	0.9%	0.4%	0.4%
Tallahassee, FL	0.4%	0.5%	0.4%	0.3%	0.3%	0.4%	0.3%	0.3%	0.1%	0.2%	0.1%	0.1%
Washington, DC	1.5%	1.5%	1.4%	1.6%	1.6%	1.6%	1.4%	1.7%	1.5%	1.6%	1.5%	1.9%
West Palm Beach, FL	0.3%	0.5%	0.4%	0.4%	0.3%	0.5%	0.4%	0.3%	0.3%	0.3%	0.2%	0.1%
Other MSAs	21.8%	22.2%	20.9%	18.5%	18.2%	18.1%	15.8%	13.8%	19.5%	16.6%	13.3%	12.6%
Not in a MSA	9.1%	8.2%	6.9%	5.0%	6.3%	5.4%	4.0%	3.5%	5.0%	3.6%	2.7%	2.4%

Table 3: Ethnic Inventors and MSA Characteristics, Weighted Estimations

	English		Chinese		Indian		European		Hispanic	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Dependent Variable is Share of 1985-2004 Ethnic Patenting in the MSA</i>										
1975-1984 Share of Ethnic Patents in MSA		0.842 (0.284)		0.865 (0.501)		0.796 (0.186)		0.646 (0.053)		0.526 (0.185)
Population Share of MSA	0.573 (0.076)	-0.132 (0.260)	0.475 (0.099)	-0.273 (0.495)	0.457 (0.199)	-0.176 (0.186)	0.650 (0.191)	0.117 (0.066)	0.812 (0.071)	0.268 (0.200)
Log Population Density of MSA	0.251 (0.105)	-0.063 (0.134)	-0.140 (0.129)	-0.253 (0.166)	0.143 (0.238)	-0.223 (0.146)	0.329 (0.211)	-0.004 (0.084)	-0.080 (0.106)	-0.100 (0.078)
Coastal Access of MSA	0.029 (0.137)	0.177 (0.161)	0.378 (0.266)	0.294 (0.160)	0.240 (0.237)	0.327 (0.221)	0.063 (0.146)	0.190 (0.132)	0.331 (0.135)	0.269 (0.106)
Share of Population with Bachelors Ed.	0.429 (0.257)	0.268 (0.163)	0.505 (0.399)	0.184 (0.163)	0.602 (0.378)	0.353 (0.253)	0.498 (0.270)	0.301 (0.201)	0.303 (0.216)	0.220 (0.174)
Share of Population under 30 in Age	-0.779 (0.566)	-0.711 (0.456)	-1.320 (1.150)	-1.031 (0.684)	-1.291 (0.980)	-1.161 (0.824)	-0.641 (0.569)	-0.667 (0.519)	-0.558 (0.535)	-0.581 (0.493)
Share of Population over 60 in Age	-0.452 (0.347)	-0.567 (0.325)	-0.757 (0.704)	-0.804 (0.535)	-0.703 (0.598)	-0.844 (0.549)	-0.175 (0.362)	-0.432 (0.326)	-0.275 (0.334)	-0.400 (0.327)
Share of Population Female	-0.313 (0.256)	-0.451 (0.268)	-0.576 (0.516)	-0.968 (0.592)	-0.090 (0.485)	-0.632 (0.489)	0.155 (0.340)	-0.295 (0.251)	-0.128 (0.247)	-0.375 (0.285)
R-Squared	0.84	0.88	0.54	0.69	0.61	0.74	0.82	0.91	0.90	0.92

Notes: Estimations provide partial correlations for ethnic patenting undertaken in 244 MSAs over the 1985-2004 period. The dependent variable is the MSA's share of indicated ethnic invention relative to the MSA sample. Explanatory regressors are from the 1990 Census of Populations, excepting coastal access and the lagged ethnic patenting share. The latter is ethnic specific and is calculated for the 1975-1984 pre-period from the ethnic patenting database. Estimations are weighted by MSA populations. Variables are transformed to unit standard deviation for interpretation. Robust standard errors are reported in parenthesis.

Table 4: Ethnic Inventors and MSA Characteristics, Unweighted Estimations

	English		Chinese		Indian		European		Hispanic	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Dependent Variable is Share of 1985-2004 Ethnic Patenting in the MSA</i>										
1975-1984 Share of Ethnic Patents in MSA		0.884 (0.255)		0.968 (0.586)		0.726 (0.262)		0.643 (0.107)		0.655 (0.271)
Population Share of MSA	0.810 (0.106)	-0.029 (0.171)	0.647 (0.145)	-0.230 (0.431)	0.684 (0.185)	0.037 (0.134)	0.845 (0.166)	0.261 (0.102)	0.901 (0.075)	0.250 (0.189)
Log Population Density of MSA	0.053 (0.034)	0.026 (0.026)	-0.047 (0.029)	-0.019 (0.039)	-0.002 (0.051)	-0.018 (0.030)	0.020 (0.050)	0.016 (0.020)	-0.043 (0.023)	-0.003 (0.015)
Coastal Access of MSA	-0.027 (0.035)	0.022 (0.039)	0.052 (0.057)	0.067 (0.047)	0.012 (0.050)	0.046 (0.055)	-0.009 (0.033)	0.020 (0.030)	0.054 (0.033)	0.043 (0.026)
Share of Population with Bachelors Ed.	0.123 (0.034)	0.091 (0.023)	0.084 (0.050)	0.041 (0.025)	0.113 (0.048)	0.087 (0.035)	0.094 (0.034)	0.080 (0.026)	0.070 (0.029)	0.067 (0.025)
Share of Population under 30 in Age	-0.151 (0.064)	-0.145 (0.056)	-0.115 (0.111)	-0.152 (0.104)	-0.139 (0.100)	-0.150 (0.091)	-0.078 (0.065)	-0.110 (0.055)	-0.045 (0.056)	-0.090 (0.061)
Share of Population over 60 in Age	-0.102 (0.051)	-0.135 (0.053)	-0.078 (0.086)	-0.151 (0.103)	-0.086 (0.078)	-0.140 (0.084)	-0.015 (0.053)	-0.081 (0.045)	-0.012 (0.047)	-0.076 (0.056)
Share of Population Female	-0.056 (0.023)	-0.050 (0.021)	-0.055 (0.037)	-0.058 (0.033)	-0.055 (0.033)	-0.057 (0.033)	-0.032 (0.021)	-0.039 (0.019)	-0.033 (0.021)	-0.042 (0.021)
R-Squared	0.79	0.85	0.45	0.65	0.54	0.64	0.78	0.86	0.83	0.87

Notes: See Table 3. Estimations are unweighted.

Table 5: Concentration Ratios of Invention

	Total Population	Total Invention	English Invention	Non-Eng. Invention	Chinese Invention	Indian Invention
A. Herfindahl-Hirschman Index						
1975-1979	0.025	0.040	0.037	0.061	0.062	0.059
1980-1984	0.024	0.037	0.034	0.055	0.066	0.051
1985-1989	0.024	0.034	0.030	0.051	0.063	0.052
1990-1994	0.024	0.032	0.028	0.048	0.068	0.046
1995-1999	0.023	0.038	0.031	0.065	0.106	0.072
2000-2004	0.023	0.040	0.030	0.075	0.119	0.075
Mean	0.024	0.037	0.032	0.059	0.081	0.059
B. Share in Top 5 MSAs from 1975-1984						
1975-1979	28.2%	37.8%	35.9%	46.7%	48.0%	43.4%
1980-1984	27.5%	35.7%	33.8%	44.0%	49.5%	40.1%
1985-1989	27.4%	33.7%	31.4%	43.0%	49.2%	41.2%
1990-1994	27.1%	32.2%	29.6%	41.2%	48.6%	38.5%
1995-1999	26.5%	33.7%	29.8%	44.6%	53.3%	43.3%
2000-2004	26.5%	33.1%	28.0%	45.1%	53.8%	41.6%
Mean	27.2%	34.4%	31.4%	44.1%	50.4%	41.4%
C. Ellison-Glaeser Index Relative to MSA Populations						
1975-1979	n.a.	0.003	0.002	0.011	0.014	0.011
1980-1984		0.003	0.002	0.010	0.019	0.011
1985-1989		0.003	0.003	0.009	0.018	0.011
1990-1994		0.004	0.004	0.010	0.027	0.012
1995-1999		0.012	0.009	0.029	0.067	0.038
2000-2004		0.016	0.010	0.041	0.082	0.047
Mean		0.007	0.005	0.018	0.038	0.022

Notes: Metrics consider agglomeration of US domestic invention across 283 MSAs, with invention in rural areas excluded. Top 5 MSAs are kept constant from 1975-1984 rankings: New York City, Los Angeles, Chicago, Philadelphia, and San Francisco. Ellison and Glaeser metrics consider agglomeration of invention relative to MSA populations. These latter metrics abstract from plant Herfindahl corrections. General population counts from 1995-1999 are used for 2000-2004.

Table 6: Concentration Ratios of Invention by Technology Group

	Chemicals	Computers & Comm.	Drugs & Medical	Electrical & Electronic	Mechanical	Miscellaneous
A. Herfindahl-Hirschman Index for All Patents Within Technology Group						
1975-1979	0.053	0.055	0.070	0.043	0.032	0.039
1980-1984	0.048	0.050	0.061	0.039	0.030	0.035
1985-1989	0.043	0.048	0.055	0.036	0.029	0.031
1990-1994	0.038	0.054	0.047	0.037	0.028	0.028
1995-1999	0.033	0.075	0.050	0.052	0.029	0.027
2000-2004	0.034	0.078	0.053	0.059	0.032	0.026
Mean	0.041	0.060	0.056	0.044	0.030	0.031
B. HHI for English Patents Within Technology Group						
1975-1979	0.049	0.051	0.063	0.040	0.030	0.036
1980-1984	0.043	0.046	0.056	0.035	0.028	0.032
1985-1989	0.038	0.043	0.050	0.033	0.027	0.028
1990-1994	0.033	0.046	0.044	0.032	0.026	0.025
1995-1999	0.029	0.059	0.046	0.038	0.026	0.023
2000-2004	0.028	0.055	0.048	0.040	0.028	0.022
Mean	0.037	0.050	0.051	0.036	0.028	0.028
C. HHI for non-English Patents Within Technology Group						
1975-1979	0.073	0.079	0.103	0.061	0.048	0.062
1980-1984	0.067	0.069	0.087	0.057	0.041	0.053
1985-1989	0.062	0.074	0.078	0.053	0.042	0.047
1990-1994	0.053	0.084	0.060	0.057	0.039	0.043
1995-1999	0.047	0.126	0.065	0.095	0.042	0.044
2000-2004	0.051	0.141	0.067	0.109	0.050	0.043
Mean	0.059	0.095	0.077	0.072	0.044	0.049

Notes: See Table 5. Patents are grouped into the major technology categories given in the column headers.

Table 7: Concentration Ratios of Invention by Institution

	Chemicals	Computers & Comm.	Drugs & Medical	Electrical & Electronic	Mechanical	Miscellaneous
A. Herfindahl-Hirschman Index for All Industry Patents						
1975-1979	0.058	0.056	0.086	0.044	0.033	0.040
1980-1984	0.053	0.050	0.076	0.040	0.031	0.037
1985-1989	0.047	0.050	0.064	0.036	0.030	0.030
1990-1994	0.042	0.056	0.054	0.038	0.031	0.027
1995-1999	0.035	0.080	0.058	0.055	0.031	0.025
2000-2004	0.037	0.082	0.061	0.064	0.037	0.025
Mean	0.045	0.062	0.066	0.046	0.032	0.031
B. HHI for All University and Government Patents						
1975-1979	0.043	0.088	0.043	0.054	0.041	0.040
1980-1984	0.039	0.068	0.046	0.050	0.039	0.040
1985-1989	0.036	0.059	0.044	0.046	0.041	0.029
1990-1994	0.033	0.049	0.047	0.052	0.040	0.031
1995-1999	0.035	0.048	0.041	0.045	0.040	0.027
2000-2004	0.033	0.044	0.038	0.042	0.039	0.029
Mean	0.036	0.059	0.043	0.048	0.040	0.033
C. HHI for non-English Industry Patents						
1975-1979	0.078	0.079	0.118	0.061	0.046	0.061
1980-1984	0.072	0.068	0.110	0.057	0.042	0.052
1985-1989	0.067	0.078	0.091	0.053	0.042	0.045
1990-1994	0.058	0.089	0.071	0.060	0.041	0.038
1995-1999	0.050	0.133	0.076	0.103	0.044	0.038
2000-2004	0.056	0.148	0.077	0.118	0.055	0.038
Mean	0.064	0.099	0.091	0.075	0.045	0.045
D. HHI for non-English University and Government Patents						
1975-1979	0.052	0.123	0.055	0.075	0.048	0.063
1980-1984	0.046	0.108	0.057	0.067	0.041	0.060
1985-1989	0.047	0.066	0.049	0.060	0.048	0.040
1990-1994	0.039	0.058	0.055	0.059	0.055	0.037
1995-1999	0.039	0.057	0.051	0.048	0.050	0.033
2000-2004	0.031	0.049	0.043	0.049	0.046	0.034
Mean	0.042	0.077	0.052	0.060	0.048	0.044

Notes: See Table 5. Patents are grouped into the major technology categories given in the column headers.

Table A1: Coagglomeration of US Ethnic Invention

	Chinese	English	European	Hispanic	Indian	Japanese	Korean	Russian	Vietnam.
A. 1975-1979 Coagglomeration of Ethnic Invention									
Chinese	0.014								
English	0.004	0.002							
European	0.011	0.004	0.014						
Hispanic	0.010	0.003	0.009	0.011					
Indian	0.011	0.004	0.012	0.009	0.011				
Japanese	0.010	0.005	0.005	0.011	0.005	0.034			
Korean	0.009	0.004	0.009	0.008	0.008	0.012	0.012		
Russian	0.011	0.005	0.012	0.011	0.011	0.012	0.010	0.015	
Vietnam.	0.011	0.004	0.009	0.012	0.008	0.020	0.010	0.013	0.024
B. 2000-2004 Coagglomeration of Ethnic Invention									
Chinese	0.082								
English	0.024	0.010							
European	0.033	0.011	0.016						
Hispanic	0.034	0.010	0.014	0.016					
Indian	0.059	0.019	0.025	0.025	0.047				
Japanese	0.082	0.024	0.032	0.034	0.058	0.084			
Korean	0.075	0.020	0.030	0.031	0.053	0.075	0.071		
Russian	0.051	0.015	0.022	0.022	0.037	0.051	0.048	0.034	
Vietnam.	0.086	0.026	0.033	0.035	0.062	0.087	0.078	0.051	0.097

Notes: Metrics consider coagglomeration of ethnic invention relative to MSA populations.

Table A2: Concentration Ratios at Sub-Category Levels

	Chemicals	Computers & Comm.	Drugs & Medical	Electrical & Electronic	Mechanical	Miscellaneous
A. Herfindahl-Hirschman Index for All Patents Within Technology Group						
1975-1979	0.053	0.055	0.070	0.043	0.032	0.039
1980-1984	0.048	0.050	0.061	0.039	0.030	0.035
1985-1989	0.043	0.048	0.055	0.036	0.029	0.031
1990-1994	0.038	0.054	0.047	0.037	0.028	0.028
1995-1999	0.033	0.075	0.050	0.052	0.029	0.027
2000-2004	0.034	0.078	0.053	0.059	0.032	0.026
Mean	0.041	0.060	0.056	0.044	0.030	0.031
B. Unweighted HHI Average Across Sub-Category Technology Groups						
1975-1979	0.057	0.059	0.072	0.051	0.044	0.052
1980-1984	0.053	0.059	0.069	0.048	0.040	0.050
1985-1989	0.050	0.064	0.063	0.046	0.042	0.042
1990-1994	0.041	0.073	0.054	0.046	0.049	0.040
1995-1999	0.039	0.095	0.057	0.057	0.048	0.041
2000-2004	0.040	0.102	0.062	0.060	0.049	0.051
Mean	0.047	0.075	0.063	0.051	0.045	0.046
C. Weighted HHI Average Across Sub-Category Technology Groups						
1975-1979	0.060	0.059	0.083	0.047	0.038	0.047
1980-1984	0.053	0.055	0.071	0.044	0.035	0.044
1985-1989	0.047	0.055	0.066	0.043	0.036	0.038
1990-1994	0.041	0.062	0.054	0.045	0.040	0.035
1995-1999	0.037	0.085	0.058	0.064	0.041	0.035
2000-2004	0.038	0.088	0.062	0.072	0.047	0.042
Mean	0.046	0.068	0.066	0.052	0.040	0.040

Notes: See Table 6.

Table A3: Descriptive Statistics for Inventors Residing in Foreign Countries and Regions

Summary Statistics for Full and Restricted Matching Procedures								
	Obs.	Percentage of Region's Inventors Matched with Ethnic Database		Percentage of Region's Inventors Assigned Ethnicity of Their Region		Percentage of Region's Inventors Assigned Ethnicity of Region (Partial)		
		Full	Restrict.	Full	Restrict.	Full	Restrict.	
United Kingdom	175,077	99%	95%	85%	83%	92%	91%	
China, Singapore	136,818	100%	98%	89%	89%	91%	91%	
Western Europe	1,137,751	97%	80%	66%	46%	73%	58%	
Hispanic Nations	24,793	98%	73%	74%	68%	93%	93%	
India	11,056	84%	77%	83%	88%	85%	89%	
Japan	1,691,337	98%	89%	100%	96%	100%	96%	
South Korea	100,140	100%	100%	83%	83%	87%	88%	
Russia	32,128	93%	80%	80%	84%	93%	94%	
Vietnam	34	100%	97%	42%	52%	50%	52%	

Complete Ethnic Composition of Region's Inventors (Full Matching)									
	English	Chinese	European	Hispanic	Indian	Japanese	Korean	Russian	Vietnam.
United Kingdom	85%	2%	5%	3%	2%	0%	0%	2%	0%
China, Singapore	2%	89%	1%	1%	1%	1%	5%	0%	1%
Western Europe	21%	1%	66%	8%	1%	0%	0%	3%	0%
Hispanic Nations	12%	1%	10%	74%	0%	1%	0%	2%	0%
India	5%	1%	2%	7%	83%	0%	0%	2%	0%
Japan	0%	0%	0%	0%	0%	100%	0%	0%	0%
South Korea	2%	12%	0%	0%	0%	1%	83%	1%	0%
Russia	5%	1%	3%	10%	0%	0%	0%	80%	0%
Vietnam	17%	24%	14%	0%	0%	3%	0%	0%	42%

Notes: Matching is undertaken at inventor level using the Full and Restricted Matching procedures outlined in the text. The middle columns of the top panel summarize the share of each region's inventors assigned the ethnicity of that region; the complete composition for the Full Matching procedure is detailed in the bottom panel. The right-hand columns in the top panel document the percentage of the region's inventors assigned at least partially to their region's ethnicity.

Greater China includes Mainland China, Hong Kong, Macao, and Taiwan. Western Europe includes Austria, Belgium, Denmark, Finland, France, Germany, Italy, Luxembourg, Netherlands, Norway, Poland, Sweden, and Switzerland. Hispanic Nations includes Argentina, Belize, Brazil, Chile, Columbia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, Philippines, Portugal, Spain, Uruguay, and Venezuela. Russia includes former Soviet Union countries.

Table A4: Most Common Ethnic Surnames for Inventors Residing in the US

Chinese	English	European	Hispanic / Filipino	Indian / Hindi					
Chan	1335	Adams	2545	Abel	180	Acosta	65	Adler	319
Chang	3214	Allen	3019	Albrecht	327	Acquaviva	58	Agarwal	184
Chao	427	Anderson	6271	Antos	220	Adell	86	Aggarwal	94
Chau	163	Bailey	1559	Auerbach	138	Alvarez	235	Agrawal	375
Chen	4306	Baker	2883	Baer	286	Arroyo	68	Ahmad	148
Cheng	1057	Bell	1677	Bauer	931	Ayer	134	Ahmed	337
Cheung	351	Bennett	1522	Beck	1094	Ayres	151	Akram	98
Chiang	584	Brown	6818	Bender	332	Bales	173	Ali	193
Chien	164	Burns	1145	Berg	933	Bartos	58	Arora	95
Chiu	427	Butler	1131	Berger	784	Blanco	71	Ash	183
Chou	513	Campbell	2339	Bodor	135	Bolanos	116	Aslam	90
Chow	468	Carlson	1542	Budzich	112	Boles	60	Badesha	90
Chu	1184	Carter	1522	Caron	188	Cabrera	62	Baliga	111
Chuang	160	Clark	3273	Cerami	117	Calderon	77	Banerjee	137
Fan	363	Cohen	1513	Chandraratna	126	Camacho	59	Basu	101
Fang	256	Cole	1228	Collette	116	Cardenas	58	Bhat	94
Feng	184	Collins	1681	Crivello	119	Carnes	69	Bhatia	172
Fong	298	Cook	1994	D'Amico	126	Castillo	61	Bhatt	105
Fu	220	Cooper	1788	Dietrich	200	Chavez	76	Bhattacharya	105
Fung	248	Cox	1370	Dietz	298	Contreras	61	Bhattacharyya	90
Guo	182	Davis	5229	Eberhardt	136	Cruz	118	Bose	159
Han	379	Edwards	1962	Eckenhoff	118	D'Alelio	69	Brunelle	116
He	194	Erickson	1191	Effland	133	D'Silva	87	Chandra	91
Ho	817	Evans	2494	Ehrlich	187	Das	409	Chatterjee	293
Hou	161	Fischer	1126	Ferrari	124	Delgado	102	Chattha	90
Hsieh	517	Fisher	1585	Fischell	161	Dias	101	Cherukuri	134
Hsu	1153	Foster	1650	Fuchs	219	Diaz	303	Chubb	90
Hu	494	Fox	1230	Gelardi	127	Dominguez	111	Datta	202
Huang	1545	Gardner	1257	Grabbe	136	Duran	87	Desai	442
Hung	317	Gordon	1500	Grasselli	135	Elias	163	Dixit	132
Jiang	281	Graham	1284	Gunther	173	Fernandes	81	Dutta	103
Kao	350	Gray	1521	Guttag	127	Fernandez	285	Fazan	107
Kung	225	Green	2051	Haas	514	Francisco	64	Gaffar	150
Kuo	600	Hall	2928	Hansen	1730	Freitas	78	Gandhi	105
Lai	466	Hanson	1289	Hartman	757	Gagnon	157	Ganguly	110
Lam	491	Harris	2838	Hartmann	220	Garcia	612	Garg	138
Lau	578	Hayes	1200	Hause	134	Garza	76	Ghosh	237
Lee	1325	Hill	2061	Hecht	142	Gomes	89	Goel	208
Leung	500	Hoffman	1433	Heinz	116	Gomez	179	Goli	100
Lew	403	Howard	1158	Henrick	123	Gonsalves	60	Gupta	851
Li	1652	Hughes	1340	Horodysky	232	Gonzales	131	Harandi	159
Liang	418	Jackson	2319	Horvath	221	Gonzalez	441	Hassan	110
Liao	194	Jensen	1227	Jacobs	1122	Gutierrez	387	Hussain	98
Lien	202	Johnson	10718	Kanner	118	Halasa	147	Imran	118
Lim	178	Johnston	1167	Kasper	155	Hernandez	324	Iyer	219
Lin	2348	Jones	6068	Kempf	144	Herrera	71	Jain	397
Ling	211	Keller	1132	Knapp	529	Herron	220	Joshi	319
Liu	1981	Kelly	1685	Knifton	201	Jimenez	90	Kamath	111
Lo	503	Kennedy	1303	Koenig	307	Konopka	62	Kapoor	145
Lu	650	King	2591	Kresge	125	Kulprathipanja	76	Khanna	210
Ma	437	Klein	1372	Kukes	123	Lee	126	Krishnakumar	97
Mao	178	Larson	1561	Lange	443	Lieb	62	Krishnamurthy	119

Table A4: Most Common US Ethnic Surnames, continued

Chinese	English	European	Hispanic / Filipino	Indian / Hindi	
Ng	451 Lee	5438 Lapeyre	161 Lomas	63 Krishnan	167
Ong	232 Lewis	2788 Laskaris	120 Lopez	377 Kulkarni	119
Pai	198 Long	1446 Lemelson	299 Machado	79 Kumar	777
Pan	444 Marshall	1213 Lorenz	198 Mares	82 Lal	175
Peng	165 Martin	4214 Ludwig	304 Marin	103 Malik	179
Shen	669 Miller	9011 Lutz	402 Marquez	75 Mathur	112
Shi	194 Mitchell	1862 Maier	319 Martinez	534 Mehra	102
Shieh	151 Moore	3572 Mayer	704 Medina	92 Mehrotra	126
Shih	513 Morgan	1663 Meyer	1815 Menard	89 Mehta	436
Shu	264 Morris	1908 Milberger	114 Mendoza	79 Menon	125
Shum	152 Murphy	1968 Mitra	140 Molina	85 Mishra	114
Sih	318 Murray	1246 Molnar	162 Molitor	71 Misra	113
Song	286 Myers	1573 Morin	170 Munoz	62 Mookherjee	271
Su	443 Nelson	3854 Mueller	1349 Nestor	96 Nair	203
Sun	691 Olson	1722 Muller	546 Nunez	66 Narang	96
Tai	178 Palmer	1145 Nagel	263 Ondetti	104 Narayanan	231
Tam	283 Parker	1976 Nilssen	213 Ortega	71 Natarajan	144
Tan	366 Peters	1200 Novak	436 Ortiz	168 Nath	102
Tang	769 Peterson	2769 Pagano	112 Padilla	66 Parekh	107
Teng	242 Phillips	2299 Pastor	204 Pallos	92 Parikh	123
Ting	213 Price	1148 Pittet	119 Pereira	87 Patel	1819
Tong	270 Reed	1625 Ponticello	126 Perez	269 Patil	188
Trinh	178 Richardson	1224 Rao	241 Pfiester	69 Prasad	240
Tsai	441 Roberts	2524 Reitz	138 Quintana	77 Puri	108
Tsang	255 Robinson	2112 Rivier	125 Ramirez	168 Qureshi	102
Tsao	218 Rogers	1770 Roman	226 Ramos	114 Rahman	133
Tseng	281 Ross	1499 Rostoker	201 Regnier	70 Raj	97
Tung	302 Russell	1476 Schmidt	2025 Reis	86 Rajagopalan	108
Wan	173 Ryan	1245 Schneider	1377 Reno	73 Ramachandran	175
Wang	3381 Scott	2191 Schultz	1230 Reyes	69 Ramakrishnan	94
Wei	428 Shaw	1535 Schulz	518 Rivera	174 Raman	95
Wong	2210 Smith	13623 Schwartz	1493 Robeson	96 Ramesh	96
Woo	354 Snyder	1402 Schwarz	418 Rodrigues	74 Rao	526
Wu	1956 Stevens	1317 Speranza	188 Rodriguez	520 Ravichandran	91
Xu	368 Stewart	1678 Spitz	119 Romero	103 Saari	93
Yan	297 Sullivan	1473 Straeter	253 Ruiz	159 Sandhu	252
Yang	1315 Taylor	4081 Theeuwes	224 Salazar	77 Shah	1115
Yao	208 Thomas	2923 Trokhan	111 Sanchez	327 Sharma	408
Yee	335 Thompson	3736 Uskokovic	124 Silva	217 Singh	914
Yeh	482 Turner	1622 Van Scott	115 Solar	70 Singhal	97
Yen	304 Walker	2758 Vock	407 Soled	59 Sinha	149
Yin	159 Ward	1679 Wachter	124 Soto	62 Sircar	171
Yu	1207 Watson	1289 Wagner	1512 Souza	95 Srinivasan	271
Yuan	236 White	3792 Weber	1646 Suarez	99 Srivastava	177
Zhang	629 Williams	5982 Weder	530 Torres	172 Subramanian	173
Zhao	223 Wilson	4650 Weiss	935 Varga	70 Thakur	118
Zheng	162 Wood	2257 Wolf	961 Vasquez	64 Varma	117
Zhou	269 Wright	2798 Zimmerman	931 Vazquez	73 Venkatesan	116
Zhu	196 Young	3593 Zimmermann	119 Vinals	231 Vora	176

Table A4: Most Common US Ethnic Surnames, continued

Japanese		Korean		Russian		Vietnamese	
Arakawa	46	Ahn	94	Aghajanian	64	Bahn	7
Asato	73	Bae	65	Anscher	44	Banh	6
Chen	36	Baek	25	Askin	39	Be	5
Doi	51	Bak	34	Avakian	35	Bearce	7
Fujii	40	Bang	34	Babler	58	Bi	35
Fujimoto	55	Bark	23	Banko	34	Bich	15
Fujioka	54	Cha	20	Barna	46	Bien	59
Fukuda	64	Chai	77	Benko	33	Bihn	7
Furukawa	35	Chin	541	Blonder	66	Bui	109
Hasegawa	96	Cho	448	Borsuk	42	Can	6
Hashimoto	72	Choe	100	Danko	52	Chich	5
Hayashi	103	Choi	322	Dombroski	37	Diem	17
Hey	33	Chon	16	Duvdevani	42	Dien	6
Higham	35	Chong	99	Elko	36	Diep	26
Higuchi	76	Choo	37	Favstritsky	44	Dinh	60
Honda	40	Chun	155	Frenkel	50	DoMinh	16
Hori	33	Chung	688	Garabedian	60	Doan	204
Hornak	53	Drozd	22	Gelfand	81	Dominh	5
Ide	111	Ewbank	21	Georgiev	41	Donlan	17
Imai	92	Eyuboglu	27	Ginzburg	62	Dotrong	8
Inoue	33	Gang	20	Gitlin	50	Dovan	26
Irick	84	Gu	118	Godlewski	38	Duan	33
Ishida	34	Hahm	18	Goralski	57	Due	6
Ishii	37	Hahn	620	Gordin	42	Duong	52
Ishikawa	59	Hansell	29	Gorin	58	Eskew	7
Ito	140	Hogle	17	Gregorian	34	Gran	11
Iwamoto	32	Hohn	19	Grinberg	64	Hoang	103
Iwasaki	48	Hone	16	Grushkin	37	Hopping	8
Izu	45	Hong	319	Grzybowski	36	Huynh	101
Kaneko	72	Hosking	24	Gurevich	45	Huynh-Ba	8
Kato	59	Hwang	517	Guzik	48	Khau	5
Kaun	32	Hyun	32	Hrib	37	Khaw	9
Kautz	64	Ih	16	Hynecek	58	Khieu	13
Kawakami	33	Im	37	Ibrahim	103	Khu	5
Kawasaki	56	Jang	94	Iranmanesh	44	Kiem	5
Kaya	44	Jeong	34	Ivanov	37	Lahue	10
Kimura	63	Ji	42	Janko	34	Laursen	19
Kino	37	Jin	175	Jastrzebski	37	Lavan	11
Kirihata	34	Joo	19	Juhasz	39	Le	415
Kiwala	132	Ju	100	Kahle	89	Le Duc	6
Kobayashi	125	Jung	205	Kaminski	254	Le Van	7
Maki	81	Kahng	17	Kaminsky	62	Leen	10
Maruyama	32	Kang	275	Kaplinsky	49	Loan	5
Matsuda	36	Kim	1987	Keritsis	35	Luong	30
Matsumoto	78	Ko	217	Khan	62	Ly	31
Matsunaga	32	Koh	40	Khandros	55	Minh	17
Miyano	54	Koo	90	Kneller	41	Nellums	12
Mizuhara	83	Kun	54	Korsunsky	80	Nghiem	5
Mori	39	Kwak	46	Kowal	57	Ngo	196
Morita	40	Kwon	156	Kozel	33	Nguyen	1514
Moslehi	103	Lee	325	Kulka	35	Nguyen-Dinh	7
Motoyama	49	Lim	82	Kurkov	35	Nguyenphu	7

Table A4: Most Common US Ethnic Surnames, continued

Japanese		Korean		Russian		Vietnamese	
Najjar	76	Mennie	33	Lapidus	34	Nho	7
Nakagawa	74	Min	71	Lee	48	Nhu	6
Nakajima	32	Minshall	18	Lisak	36	Nieh	53
Nakamura	74	Nam	18	Lopata	50	Nim	12
Nakanishi	46	Nevins	24	Lukacs	37	Ninh	8
Nakano	53	Nyce	18	Lysenko	39	Pham	286
Nakao	41	Oh	151	Magnotta	35	Phy	19
Nemoto	50	Paek	25	Mankovitz	34	Postman	8
Nishimura	32	Paik	82	Messing	47	Quach	24
Nishioka	43	Pak	64	Metlitsky	81	Quy	6
Noda	48	Park	912	Mikhail	70	Roch	26
Ogawa	39	Quay	58	Milkovic	46	Sien	6
Ogura	57	Rhee	120	Minaskanian	39	Sinh	7
Ohkawa	48	Rhim	17	Mooradian	50	Ta	39
Okada	37	Rim	30	Nadelson	92	Takach	11
Okamoto	62	Ronen	19	Nappholz	38	Tau	7
Okumura	45	Ryang	24	Narayan	203	Thach	11
Ono	34	Ryu	46	Neuwirth	42	Thai	16
Ovshinsky	194	Sahm	24	Onopchenko	59	Thiem	10
Saito	49	Sahoo	22	Orloff	36	Thut	16
Sasaki	70	Sellstrom	23	Papadopoulos	47	Tiedt	6
Sato	134	Seo	18	Pinchuk	62	Tiep	11
Seto	37	Sheem	21	Pinsky	34	Tietjen	32
Shibata	52	Shim	101	Raber	45	To	7
Shida	45	Shin	149	Rabii	34	Ton-That	6
Shimizu	32	Shinn	64	Rabinovich	52	Tran	631
Shinkai	48	Sim	43	Rubsamen	47	Trandai	7
Shoji	45	Sjostrom	18	Sahatjian	40	Trang	12
Sigmund	35	So	149	Sarkisian	35	Trank	7
Suto	33	Sohn	42	Sarraf	38	Tri	7
Suzuki	152	Son	72	Schwan	77	Trieu	8
Takahashi	81	Sue	36	Simko	70	Trong	7
Takekoshi	50	Suh	188	Sipos	38	Truc	8
Takeuchi	61	Suk	23	Skowronski	44	Tu	190
Tamura	50	Sung	255	Smetana	42	Tuten	19
Tanaka	191	Uhm	16	Sofranko	61	Tuy	14
Ueda	34	Um	22	Sorkin	52	Ty	21
Wada	47	Whang	40	Stanko	37	Van	18
Watanabe	140	Won	48	Tabak	85	Van Cleve	30
Yamada	62	Yi	56	Tepman	41	Van Dam	8
Yamaguchi	42	Yim	55	Terzian	75	Van Le	18
Yamamoto	178	Yohn	16	Tsinberg	38	Van Nguyen	11
Yamasaki	42	Yoo	133	Tults	34	Van Pham	8
Yamashita	32	Yoon	405	Uram	43	Van Phan	27
Yasuda	50	You	58	Vartanian	42	Van Tran	13
Yasui	51	Yuh	40	Veltman	39	Vo	95
Yokoyama	52	Yum	69	Warchol	34	Vo-Dinh	19
Yoshida	127	Yun	68	Wasilewski	34	Vu	141
Yuan	40	Zhu	24	Welsch	44	Vuong	33