Immigrants and the Spatial Reallocation of US Invention

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Abstract

This study investigates the extent to which immigrants facilitate the spatial reallocation of invention and related entrepreneurship across US cities. A 10% increase in ethnic invention for a technology is associated with a 1% increase in the rate of spatial reallocation of invention for the technology across US cities. The causal direction of this association is confirmed through regressions that interact national immigration trends with initial dependency on immigrants by technology. Similar results are also found when looking at an exogenous surge in Chinese and Indian scientific immigration after the Immigration Act of 1990.

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

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

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1 Introduction

Immigrants play a very important role in US technology development and commercialization.[1] In terms of levels, immigrants represented 24% and 47% of the US science and engineering (SE) workforce with bachelor's and doctorate educations in the 2000 Census, respectively. This contribution was significantly higher than the 12% share of immigrants in the US working population. Moreover, much of the recent growth in the US scientific workforce has come through immigrant scientists and engineers (ISEs).

This study investigates the role of ISEs in facilitating the spatial reallocation of invention and related entrepreneurial activity across US cities. The San Francisco Bay Area is at the forefront of innovation and entrepreneurship in semiconductors. This was not always the case, however, and Saxenian (1994) describes the reallocation of semiconductor activity from Boston to Silicon Valley. What role does immigration play in the speed of reallocations similar to this one? Are ISEs important in the rapid development of innovation and entrepreneurship in cities like Austin, TX, and Boise City, ID? This study investigates whether technologies and industries that rely heavily on ISEs are more sensitive to high-skilled immigration inflows.

There are several reasons to suspect that ISEs may speed spatial reallocations. First, many ISEs are hired from abroad for specific needs by firms. The intent of the H-1B program, for example, is to allow firms to bring in skilled foreign workers for a specific occupation *and* location where local labor markets are constrained. Roughly 60% of visas in this program are granted to SE and computer-related occupations. Firms also have the capacity to direct where immigrant workers are to locate under a number of other temporary visa categories. If an innovative industry is expanding rapidly in one city, perhaps even outstripping the existing supply of SEs, then firms within that industry may turn to bringing in foreign talent to aid the expansion. This international sourcing may be easier or cheaper for firms than attracting the internal migration of native SEs, especially when the city in question is viewed as a less attractive option by native workers. Moreover, the legal attachment of many temporary ISEs to their sponsoring firms make it easier for the firms to retain inventors in their selected cities.[2]

Second, immigrants may have greater flexibility in where they locate even if their visa status does not require them to locate in a particular city. This can be particularly true for graduating foreign students from US universities, which is a primary source for expansions of the US SE workforce. If not returning to their home countries, the immigrants may a weaker geographic preference across US regions than natives. Likewise, direct permanent residency admissions

[1] For example, Stephan and Levin (2001), Saxenian (2002), Wadhwa et al. (2007), Hunt and Gauthier-Loiselle (2008), Kerr and Lincoln (2008), and Hunt (2009).

[2] This city-specific phenomena closely relates to the company towns described in Agrawal et al. (2009). Glaeser et al. (2009) and Klepper (2009) discuss the formation and growth of clusters more generally.

may have been attracted by specific job opportunities with less attention to initial location. Weighing against these factors is that immigrants may favor ceteris paribus being in cities that have a larger population of their ethnicity or are relatively closer to their home country (e.g., West Coast of the US for Asian immigrants). More generally, however, Borjas (2001) finds immigrants "grease" the wheel of the labor market by responding faster than natives to regional differences in economic opportunities. Borjas finds that new immigrants make up a large fraction of the marginal workers who shift across areas in response to wage differentials.[3]

The above explanations mostly center on pull rationales—immigrants meeting an exogenous increase in demand for SE talent that has sprung up in cities. Feedback mechanisms may also exist. If ISEs promote technology development in one city, they may also attract future SEs to that location (natives or immigrants). This would be especially true if immigrant entrepreneurship leads to subsequent job creation. Many observers note the feedback effects of ISEs in the continued expansion of the Silicon Valley's innovation and entrepreneurship.

To investigate these questions, we determine the probable ethnicity of all inventors receiving a patent from the US Patent and Trademark Office (USPTO) from January 1975 to May 2008. Each patent record lists one or more inventors, with 8 million inventor names associated with the 4.5 million patents. We map 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. 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.

We first review descriptive evidence on the role of ethnic inventors for US technology development and recent trends in the spatial clustering of US innovation. The data show a remarkable increase in the share of US patenting performed by inventors with non-English names between 1975 and 2004. In addition to becoming a larger share of the US inventor population, these ethnic inventors are also becoming more spatially concentrated themselves. These patterns are especially true for Chinese and Indian inventors. The combination of increasing SE contributions and greater ethnic clustering helps stop and reverse long-term declines in overall inventor agglomeration evident in the 1970s and 1980s. Descriptive tabulations suggest these observations may be linked, as the cities that have experienced the most rapid patenting growth during the last three decades are also those that have witnessed the most substantial shift in their inventor populations towards ISEs, especially those of Chinese and Indian ethnicities.

[3] On the other hand, entrepreneurship has a distinct local bias to it. Native entrepreneurs are more likely to open their businesses in their home towns than native wage workers are to be working in their home towns. See Figueiredo et al. (2002), Michelacci and Silva (2007), Buenstorf and Klepper (2007), and Dahl and Sorenson (2007, 2009).

The third section moves from the descriptive evidence to quantifying whether faster spatial reallocation of innovation across US cities is facilitated by ISEs. We examine 286 technologies at the USPTO patent class level from 1975 to 2004. Panel estimations find that a 10% increase in non-English invention for a technology is associated with a 1% increase in the amount of spatial reallocation from the previous period. This reallocation effect is particularly strong in growing industries, but it is not strongly associated with technologies shifting towards greater or weaker spatial concentration. This elasticity is robust to a variety of sample decompositions and to including detailed controls for the period-by-period shifts of 36 broader technology groupings.

While informative, this association does not establish a causal relationship due to reverse causality concerns or potential omitted variable biases. As a second test, we use variation across technologies in the extent to which they initially relied on ISEs in 1975-1979. We find that technologies with greater initial dependency experience proportionately more rapid reallocation than less dependent technologies when national expansions in non-English invention are strongest. A 10% increase in non-English invention nationally is associated with a 1% increase in the rate of spatial reallocation in the most dependent 20% of technologies relative to the least dependent technologies. This effect is particularly strong in technologies related to the semiconductors industry, but this case study generalizes more broadly. This exercise confirms that the OLS effect holds after removing the most worrisome endogeneity.

Even in the interaction regressions, however, it could be argued that particularly influential high-tech firms may overly influence national scientific immigration through lobbying efforts. To address this concern, we look at changes in Chinese and Indian SE immigration following the Immigration Act of 1990. This Act was a substantial reform of the US immigration system and led to an exogenous increase in Chinese and Indian high-skilled entry in the years immediately following. We construct a second interaction estimator based upon the effective quotas for countries before and after the reform. These reduced-form exercises again suggest that exogenous expansions in Chinese and Indian SE immigration promote faster spatial reallocation in industries that are dependent upon these workers.

Section 5 quantifies whether the spatial pattern of urban entrepreneurship is also influenced by this greater inventor mobility. While innovation is often linked to entrepreneurship, there are reasons that entrepreneurship may not quickly follow the reallocation of invention measured here. Most immigrant inventors are employed in larger corporations, especially if their entry is sponsored by a firm. This may dampen the impact for entrepreneurship compared to the invention response evident in the patenting data. We investigate using Census Bureau data the industry-level reallocation of startups and facility expansions by existing firms across cities. <Results TBD>

The final section concludes. It is well documented that ISEs have a substantial impact on US innovation. Most research on this phenomena focuses on determining the size of these contributions and the potential crowding-in or crowding-out of natives.[4] This paper is a first step for understanding whether these inflows aid in the faster spatial reallocation of innovation. This is interesting in its own right, but it is also important for understanding how we should evaluate the welfare consequences of immigration. Native crowding-in or crowding-out can be spatially separate if reallocation is occurring. This study is also important for the urban economics and innovation literature. The local nature of knowledge flows is frequently noted, making the spatial clustering of invention and related entrepreneurship important.[5] The pace of immigration may influence the speed of regional adjustments and convergence. We hope that future work can further clarify the role of immigrants in these mechanisms.

2 Patterns of US Invention 1975-2004

This section describes the central data employed in this study. We begin with an account of how the ethnic composition of US inventors has changed since 1975. We then present descriptive evidence on the spatial clustering of US invention and the role of ethnic inventors in recent shifts. We close with some simple tabulations that suggest ethnic inventors are important for the reallocation of invention across US cities.

2.1 The Ethnic Composition of US Invention

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, and Griliches (1990) surveys the use of patents as economic indicators of technology advancement. 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,

[4] For example, Friedberg and Hunt (1995), Card (2001), Borjas (2003, 2004), Matloff (2003), Hunt and Gauthier-Loiselle (2008), and Kerr and Lincoln (2008).

[5] For example, Jaffe et al. (1992), Thompson and Fox-Kean (2006), Carlino et al. (2006), Rosenthal and Strange (2003), Arzaghi and Henderson (2008), Glaeser and Kerr (2008), and Ellison et al. (2009).

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, respectively. 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.

Table 1 describes the 1975-2004 US sample. We only employ in this paper patents with inventors who are residing in the US at the time of their patent application. When multiple inventors exist on a patent, we make individual ethnicity assignments for each inventor and then discount multiple inventors such that each patent receives the same weight. The trends in Table 1 demonstrate a growing ethnic contribution to US technological 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, 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.[6]

Figure 1 illustrates the evolving ethnic composition of US inventors from 1975-2004. The omitted English share declines from 83% to 70% 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 5%, 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.

Among the other ethnicities, the Hispanic contribution grows from 3% to 4% 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

[6]The 1975-2004 statistics employ patents granted by the USPTO through May 2008. Due to the long and uneven USPTO review process, statistics are grouped by application year to 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 2008. 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.

0.3% to 1.1% over the thirty years, while the Russian climbs from 1.2% 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 0.6% to 1.0%. Finally, while the Vietnamese contribution is the lowest throughout the sample, it does exhibit the strongest relative growth from 0.1% to 0.6%.

Figure 2 groups patents into six broad categories of technologies: Chemicals, Drugs, Computers, Electrical, Mechanical, and Others. The figure sums non-English invention in these categories. The strong growth of non-English contributions in high-tech versus traditional technologies is clearly evident. Figures 3 and 4 provide a more detailed view of Chinese and Indian contributions by 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.

2.2 Spatial Clustering of US Ethnic Inventors

We next turn to simple statistics on the spatial clustering of US innovation. The appendix lists major US cities and their shares of total invention, non-English invention, and Chinese and Indian invention. We define cities through 281 Metropolitan Statistical Areas.[7] Not surprisingly, total invention 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 invention is more concentrated than general innovation. The 1995-2004 non-English inventor 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 invention. Indian and Chinese invention is even further agglomerated. San Francisco shows exceptional growth from an 8% share of total US Indian and Chinese invention in 1975-1984 to 25% in 1995-2004, while the combined shares of New York and Chicago decline from 22% to 13%.

Figure 5 documents the Herfindahl-Hirschman Index (HHI) of concentration for industrial invention in US cities.[8] This figure first highlights that US invention is more concentrated that

[7] We use the most frequent city when multiple inventors are present. Ties are further broken by the order of inventors on the patent filing. 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.

[8] This metric is defined by $HHI_t = \sum_{c \in C} Share_{ct}^2$, where C indexes 281 cities and $Share_{ct}$ is the share of patenting in city c and period t. Of course, patenting is undertaken outside of cities, too. The share of patenting outside of these 281 cities declines from 9% in 1975-1984 to 7% in 1995-2004. Patenting outside of urban areas is

the general population across urban areas. 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.[9]

Moving from the levels to the trends evident in Figure 5, 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.

Figure 6 breaks these trends down by the six major technology categories. The sharpest changes toward greater agglomeration are in the Computers and Electrical categories. It is interesting to compare the shifting patterns for industrial invention, evident in Figure 6, with the patterns for university and government invention. The latter institutions are generally constrained from agglomerating, and Figure 7 shows the patterns evident for industrial invention are not repeated in this group.

The patterns documented in these figures suggest that ethnic inventors may play an important role in the spatial allocation of US invention. First, ethnic inventors are becoming a larger share of the US inventor population. Second, these inventors are becoming more spatially concentrated themselves. These patterns are especially true for Chinese and Indian inventors. The combination of increasing contributions and greater ethnic clustering is partially responsible for the stopping and reversing of long-term declines in overall inventor agglomeration evident in the 1970s and 1980s.

This evidence, however, is incomplete. These figures first do not account for changes in patenting rates by technologies over time. Greater relative patenting by a spatially concentrated technology group can shift the aggregate distributions even if the clustering of each technology group is constant. Likewise, the rise of software patents has not been modelled. Kerr (2008b)

excluded from this paper. Kerr (2008b) shows that Ellison and Glaeser metrics yield similar general conclusions to the HHI metrics.

[9] Calculations from the 1990 and 2000 Census of Populations find that the aggregate concentration of ISEs 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 ISE shares.

provides additional descriptive evidence on these issues, concluding that these additional factors contribute to the aggregate trends but do not fully explain them. The remainder of this paper focuses on the specific question of whether ethnic inventors facilitate the reallocation of invention across US cities.[10]

2.3 Ethnic Inventors and Invention Rank by City

We next present some tabular evidence about whether ethnic inventors aid shifts in city patenting. We begin by looking at the largest patenting cities and then provide statistics for the full sample of cities. Table 2 lists 19 cities ordered by their patenting rank in 1995-2004. These 19 cities are the union of the top 15 patenting cities in 1975-1984 and the top 15 cities in 1995-2004. While the top eight cities are generally stable, subject to repositioning, the next seven cities show greater turnover. The new entrants in 1995-2004 are Austin, TX, San Diego, CA, Seattle, WA, and Boise City, ID, while the four cities exiting the top 15 are Cleveland, OH, Cincinnati, OH, Albany-Schenectady-Troy, NY, and Pittsburgh, PA. The first set of three columns provides these two rankings and the rank changes evident.

The second set of three columns documents the share of each city's invention that is undertaken by English ethnicity inventors during the two periods. The secular decline in relative English invention is clearly evident in this sample. All 19 cities exhibit a lower share of English invention in 1995-2004 than earlier, with an average decrease of -10%. This is not a mechanical outcome but instead evidence of the pervasive growth in ethnic invention. The next set of three columns repeats this tabulation for Chinese and Indian inventors, while the last set of three columns considers other non-English ethnicities. All of these shares are relative to the specific city, so they sum to 100%, and the changes likewise sum to 0%. Similar to the English decline, the relative contribution of Chinese and Indian inventors increases for all 19 cities in the sample. The relative contribution of other ethnic groups increases for most cities as well, but some declining shares are evident.

We can take some suggestive evidence for the role of ethnic inventors in shifting location patterns from these tabulations. The bottom of the table shows that cities that increase their rank exhibit on average a larger increase in Chinese and Indian inventors (+10.2%) than cities that lose rank (+6.5%). Note that this is not due to convergence or mean reversion. The cities that lose rank start with a higher Chinese and Indian inventor share, but the cities that improve rank end the sample period with the larger share. By looking at workforce compositions, these

[10] Agrawal et al. (2008a,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.

tabulations are also not keying in on changes in city patenting rates, city populations, or similar. The fractions suggest that cities increasing their patenting share underwent simultaneous shifts towards greater patenting by Chinese and Indian inventors. The overall correlation between rank change and Chinese and Indian invention growth is 0.6.

The last three columns show that other non-English inventors play a smaller but positive role, too. A 2.5% differential is evident between cities improving rank and those declining, which is less than the 3.8% differential for Chinese and Indian invention. This is remarkable as the aggregate initial size of the other ethnic inventor group is almost three times the initial size of the Chinese and Indian group (13.6% versus 5.2%).

Table 3 broadens the lens to all 281 cities. We present the same summary statistics, dividing cities into above and below median growth in invention. Faster growth is again associate with a more dramatic shift in the ethnic composition of a city's workforce towards Chinese and Indian inventors. The comparison of Panels A and B show again that this role for Chinese and Indian inventors in spatial reallocation is stronger for industrial invention than for university and government invention. The latter, in fact, appear to be facilitated more through growing contributions by other ethnicities. We now turn to empirical estimations to study these relationships more deeply.

3 OLS Empirical Results

This section presents our core empirical results. We first define our measure of the spatial reallocation of invention across US cities. We then use panel estimations to quantify the association between growth in immigrant inventor contributions and faster spatial reallocation by technology. We close the section by constructing a second specification that interacts initial dependency on ISEs by technology with national growth immigrant scientific contributions.

3.1 Spatial Reallocation

We measure the period-by-period spatial reallocation of invention across US cities for technology i through

$$\text{REALL}_{i,t} = \sum\nolimits_{c \in C} \frac{abs\left(\text{INV\%}_{c,i,t} - \text{INV\%}_{c,i,t-1}\right)}{0.5 * \left(\text{INV\%}_{c,i,t} + \text{INV\%}_{c,i,t-1}\right)}, \tag{1}$$

where $\text{INV\%}_{c,i,t}$ is the share of technology i's patents for the period t filed by inventors in city c. The sum of INV% across cities is thus 100% for each technology. $\text{REALL}_{i,t}$ sums the absolute changes in each city's share of the technology's invention from the previous period. Before summing, each of these changes are normalized by the city's average share of the technology's patents for the two periods. Normalizing by the mean share, relative to the initial or ending shares, minimizes the influence of outliers and mean reversion.

This measure (1) is motivated by the job reallocation work of Davis et al. (1996) and Autor et al. (2007). Several properties are important to note. First, the metric is orthogonal to growth in technology size as we only consider shares of invention in cities. This share approach is not essential, however, and we obtain similar results when using raw inventor counts. Second, $\text{REALL}_{i,t}$ captures new immigration to the US that is not proportional to existing inventor concentrations. The term reallocation often connotes movements of existing activity from one location to another. Our measure captures this phenomena when, for example, an existing inventor moves to a new city. The measure (1), however, also captures changes in inventor populations due to new inventors (i.e., the extensive margin). Indeed, the rationales outlined in the introduction emphasize that much of the invention reallocation associated with ISEs comes in initial location decisions or firm hiring (e.g., the H-1B program). Thus, reallocation in the context of this paper measures how the spatial distribution of inventors for a technology in one period differs from the pervious period.[11]

To calculate $\text{REALL}_{i,t}$, we group US patents into five-year blocks by technology stretching from 1975-1979 to 2000-2004. Technologies are classified at the patent class level of the USPTO system. Examples include "Refrigeration", "Chemistry: Electrical and Wave Energy", and "Cryptography". Technologies must have at least 100 US domestic patents in each time period to be included, resulting in 286 technologies. As an example, the reallocation measure would thus calculate how dissimilar the spatial allocation of "Electrical Resistors" patents filed in 1980-1984 is to the spatial allocation in 1975-1979 for the technology. The differences across subsequent five-year blocks are similarly calculated. As we cannot calculate $\text{REALL}_{i,t}$ for 1975-1979, the resulting technology-period data structure has 1430 observations from crossing five time periods with 286 technologies.

3.2 OLS Estimation

We first quantify the OLS relationship between ISEs and the spatial reallocation of invention using panel data models,

$$\ln(\text{REALL}_{i,t}) = \phi_i + \eta_t + \beta \cdot \ln(\text{ISE}_{i,t}) + \epsilon_{i,t}, \tag{2}$$

[11] The ethnic patenting data cannot reliably separate changes on the extensive and intensive margin as unique inventors are not identified (only inventor names are given). For example, the presence of more patents filed by inventors with the surname "Gupta" in San Francisco in a period can represent new SE immigration to the city, the shift of some existing inventors with that surname from other US cities, or changes in patenting productivity by inventors with that surname already in San Francisco. Thus, this study measures the net changes in spatial distributions of inventors from one period to the next by technology.

where ϕ_i and η_t are vectors of technology and year fixed effects (FEs), respectively. Technology FEs control for fixed differences across technologies in their reallocation levels and dependency on immigrant inventors. Year FEs control for longitudinal changes in reallocation rates that are common across industries. These common trends could be due to differences in regional population growth, for example. Year FEs also control for overall growth in ISE contributions. The β coefficient thus estimates the elasticity between growth in immigrant contributions by technology and greater spatial reallocation of the technology's inventors. Regressions are weighted by the mean log patenting of technologies and report standard errors clustered cross-sectionally by technology.

We measure ISE$_{i,t}$ as the non-English invention by technology-period. Ethnic inventor populations measured through patents approximate unobserved immigrant inventor counts if the propensity to patent behaves in regular ways. For example, allow observed patenting to take the form, $ISE_{i,t} = \Upsilon_i \cdot \Upsilon_t \cdot ISE_{i,t}^{Pop} \cdot \varepsilon_{i,t}$, where $ISE_{i,t}^{Pop}$ is the true population of immigrant inventors, Υ_i and Υ_t are technology and period shifters, and $\varepsilon_{i,t}$ is an idiosyncratic error term. This formulation allows for long-term differences across technologies in their patent rates and for longitudinal changes in patenting rates common to all industries (e.g., due to changing USPTO procedures). Due to the log form of specification (2), both shifters are captured by the panel effects. More generally, unmodeled patenting differences orthogonal to $ISE_{i,t}^{Pop}$ are absorbed into the error term $\epsilon_{i,t}$ without biasing the β coefficient. We further test below scenarios where this formulation may not hold.[12]

Column 1 of Table 4 presents the base regression. A 10% growth in the non-English invention of a technology is associated with a 1% greater spatial reallocation. This effect is statistically significant and economically meaningful in size. Column 2 separates non-English invention into four simple groupings: Chinese and Indian, Other Asian, European and Russian, and Hispanic inventors. Other Asian invention includes Japanese, Korean, and Vietnamese invention. This regression finds the strongest impact among Chinese and Indian inventors, followed by European and Russian inventors. The relative importance of Chinese and Indian inventors is consistently found in a number of specification variants (e.g., using ethnic shares by technology as the primary explanatory variable).

Column 3 includes a vector of technology group x period FEs, where technologies are grouped by 36 USPTO sub-categories. Examples of sub-categories include "Resins", "Optics", and "Semiconductor Devices". This specification provides very similar results to Column 1. This suggests that the observed relationship is not due to general shifts occurring at the broader sub-category level. This stability also provides greater confidence in our use of ethnic patents

[12] External data sources (e.g., Census of Populations, SESTAT) do not document immigrant inventor contributions with sufficient detail or frequency to construct ISE$_{i,t}$ directly. These data limitations are compounded by the long time considered in this work.

to model inventor populations. While it is likely that patent propensities have changed differentially across sectors during the last two decades, these differential effects would be captured by the additional controls.

Columns 4 and 5 quantify the heterogeneity in the sample. We first interact the non-English invention regressor with an indicator variable for technologies exhibiting above-median invention growth from 1975-1979 to 2000-2004. The association between ISEs and spatial reallocation is strongest in faster growing technologies. While a positive effect is evident for technologies growing at less than the median rate, the interaction term is approximately 150% stronger. On the other hand, Column 5 interacts the non-English invention regressor with an indicator variable for technologies exhibiting growing spatial concentration from 1975-1979 to 2000-2004. The association of ISEs and spatial reallocation is not dependent upon whether the technology is moving towards greater or weaker spatial concentration. The final two columns show the results are robust to dropping "Semiconductor Device" patents (sub-category 46) and software patents.[13]

3.3 Interaction Estimation

Table 4's analysis finds a strong association between ISEs and the spatial adjustment rates of technologies. A clear concern, however, is whether these estimates are driven by reverse causality or omitted variable biases. Our first test of this looks at whether technologies that were more dependent upon ISEs initially exhibit greater sensitivity to national changes in ethnic invention rates in terms of their spatial reallocation. We define sensitivity as the fraction of the technology's patents in 1975-1979 that are non-English inventors (ISE_{i,t_0}). This fraction averages 17% and ranges from 9% for "Railway Rolling Stock" (105) to 31% for "Chemistry: Natural Resins or Derivatives" (530). The national level in ISE patenting is measured directly from the ethnic patenting data as the sum over urban areas during the period.

The linear specification takes the form,

$$\ln(\text{REALL}_{i,t}) = \phi_i + \eta_t + \beta \cdot [\ln(\text{ISE}_{i,t_0}) \cdot \ln(\text{ISE}_t)] + \epsilon_{i,t}, \tag{3}$$

where the main effects are controlled for by the technology and year FEs. This empirical strategy identifies off of non-linear changes in $\text{REALL}_{i,t}$ among more dependent technologies compared to less dependent technologies. After including the panel FEs, the residual interaction

[13] Software patents are provisionally defined as patent classes greater than 700. This exclusion has very little effect on the results as most of the recent patent classes do not meet our threshold of 100 patents or more in each five-year period from 1975 onwards. Current work is attempting to isolate software patents that are classified in earlier technology categories. For example, Graham and Mowery (2004), Hall (2005), and Hall and MacGarvie (2008).

of the national ethnic patenting trend and the initial dependency of each technology can be treated as exogenous under the assumption that the national ethnic patenting trend is exogenous. This condition may not hold, however, if firms in a handful of dependent technologies are very influential in determining national immigration policies. Semiconductor Devices may have such influence, so we will empirically test its importance below. We log the interaction terms to remove scale dependency.

Table 5 presents the results for specification (3) in a format similar to Table 4. The first column finds a positive and statistically significant coefficient, suggesting that inventor reallocation is relatively higher in dependent technologies when non-English patenting is expanding nationally.

The resulting β coefficient does not have a simple interpretation in specification (3), so the appendix presents a quintiles specification that models the distribution of treatment effects. We group the 286 technologies into five quintiles based upon their initial dependency on ISEs. While high-tech patents tend to fall into more dependent quintiles, the distributions do overlap. The most dependent quintile includes at least three technologies from each of the six broad technology categories employed in Figure 2. Our augmented specification takes the form

$$\begin{aligned} \ln(\text{REALL}_{i,t}) \quad = \quad & \phi_i + \eta_t \\ & + \beta_1 \cdot [I_i(\text{Top Quintile}) \cdot \ln(\text{ISE}_t)] \\ & + \beta_2 \cdot [I_i(\text{2nd Quintile}) \cdot \ln(\text{ISE}_t)] \\ & + \beta_3 \cdot [I_i(\text{3rd Quintile}) \cdot \ln(\text{ISE}_t)] + \epsilon_{i,t}. \end{aligned} \tag{4}$$

In this design, $I_i(\cdot)$ are three indicator variables for whether technology i is in the 3rd, 2nd, or most dependent quintiles. The bottom two quintiles, accounting for 40% of technologies, serve as the reference group. Effects for the top three quintiles are measured relative to this group. This flexible specification thus tests whether reallocations in technologies thought to be reliant on immigrant inventors are more or less sensitive to changes in national ISE trends. Main effects are again absorbed into the panel FEs, with only the residual variation is exploited for identification.

The coefficients from specification (4) are reported in the appendix. They suggest that a 10% increase in ISEs nationally is associated with 1% increase in relative spatial reallocation of inventors in the most dependent quintile compared to the reference category. This effect is statistically different from the reference category and of reasonable economic magnitude. While the β_2 and β_3 coefficients for the second and third quintile are also positive, these differentials from the reference category are not statistically significant. This pattern suggests that immigration inflows have a very powerful effect for reallocation among the most dependent sectors.

The remainder of our analysis continues with the linear specification (3), with patterns in the quintiles framework similarly tracking.

The second column of Table 5 disaggregates the non-English interaction into the four groupings used earlier. Each interaction is constructed exactly the same as the core non-English interaction in Column 1. For example, the national trend in Chinese and Indian invention is interacted with each technology's initial dependency upon Chinese and Indian inventors. The reallocative force is again particularly evident for Chinese and Indian inventors.

The remaining columns of Table 5 find mostly similar results when considering the other specification variants. One noticeable difference from Table 4 is that the results are less sensitive to whether the technology is experiencing above-median growth or not. This greater stability reflects the use of pre-determined variation for identification rather than contemporaneous immigrant trends. A second difference is that the results are more sensitive to excluding technologies associated with Semiconductor Devices. The elasticity loses one-third of its economic magnitude when this sub-category is excluded. This sensitivity reflects the very high initial dependency for immigrants in this technology area.[14]

4 Immigration Quotas Exercises

The above interaction specifications suggest that greater SE immigration facilitates faster spatial reallocation of patenting across US cities among dependent industries relative to less dependent industries. This analysis is limited, however, in several ways. First, reverse causality may result in the national growth in Chinese and Indian invention not being strictly exogenous even conditional on the panel FEs. High-tech industries, for example, may be able to lobby successfully for greater immigration when they need additional workers to expand locations. It is also somewhat unsatisfying to model the national growth using patent data directly. This section prepares an estimator from US immigration quotas to help with these concerns.

4.1 The Immigration Act of 1990

The US immigration system significantly restricted the inflow of ISEs from certain nations prior to its reform with the Immigration Act of 1990 (1990 Act). This section uses the quotas surrounding this reform to model an exogenous surge in the number of Chinese and Indian ISEs.

[14] In another test of spatial concentration, we interacted the technology's initial spatial concentration with the national trend in immigrant patenting as a second explanatory variable. Technologies that are more concentrated in the initial period show greater changes in spatial reallocation with the immigration inflow. The primary interaction regressor, however, retains almost all of its original economic magnitude and statistical precision.

At its broadest levels, permanent residency admissions are made through both numerically restricted categories, governed by the quotas discussed in this section, and numerically unrestricted categories (e.g., immediate relatives of US citizens). While the latter, unrestricted category admits a little less than 60% of all immigrants, most ISEs obtain permanent residency through numerically restricted categories (75%). ISE inflows through the unrestricted categories are stable in the years surrounding the 1990 reform, so we concentrate on the numerically restricted grouping.

US immigration law applies two distinct quotas to numerically restricted immigrants. Both of these quotas were increased by the 1990 Act, and their combined change dramatically released pent-up immigration demand from ISEs in constrained countries. The first quota governs the annual number of immigrants admitted per country. This quota is uniform across nations, and the 1990 Act increased the limit from 20,000 to approximately 25,620.[15] Larger nations are more constrained by country quotas than smaller nations and benefited most from these higher admission rates. Second, separately applied quotas govern the relative admissions of family-based versus employment-based immigrants. Prior to the 1990 Act, the quotas substantially favored family-reunification applications (216,000) to employment applications (54,000). The 1990 Act shifted this priority structure by raising employment-based immigration to 120,120 (20% to 36% of the total) and reducing family-based admissions to 196,000.[16] Moreover, the relative admissions of high-skilled professionals to low-skilled workers significantly increased within the employment-based admissions.

The uniform country quotas and weak employment preferences constrained high-skilled immigration from large nations, and long waiting lists for Chinese, Indian, and Filipino applicants formed in the 1980s. When the 1990 Act simultaneously raised both of these quotas, the number of ISEs entering the US dramatically increased. Figure 8 uses records from the Immigration and Naturalization Service (INS) to detail the response. It plots the number of ISEs granted permanent residency in the US from 1983-1997 for selected ethnicities (summed over countries within each ethnicity). Prior to the 1990 Act, no trends are evident in ISE immigration. The 1990 Act took effect in October 1991, and a small increase occurred in the final three months of 1991 for Chinese and Indian ISEs. Immigration further surged in 1992-1995 as the pent-up demand was released. On the other hand, Kerr (2008a) shows that low-skilled immigration from China and India did not respond to the 1990 Act.[17]

[15] The worldwide ceiling for numerically restricted immigration now fluctuates slightly year-to-year based on past levels; maximum immigration from a single country is limited to 7% of the worldwide ceiling.

[16] The employment limit increased to 140,000, but 120,120 corresponds to the previously restricted categories.

[17] Immigration trends are developed from immigrant-level INS records. The permanent residency admissions include ISEs already working in the US on temporary visas. The trends for "new arrival" ISE are very similar. Temporary visas can only be renewed once, so the total shift in ISE population should include workers gaining permanent residency. The analysis below does not depend on this distinction. Science and engineering categories are defined as Engineers, Natural Scientists, and Mathematical and Computer Scientists; low-skilled categories are Administrative Support, Farming, Laborer, Precision Production and Repair, Service, and Sales occupations.

The extremely large Chinese response and sharp decline is partly due to a second law that slightly modified the timing of the 1990 Act's reforms. Following the Tiananmen Square crisis in June 1989, Chinese students present in the US from the time of the crisis until May 1990 were permitted to remain in the US until at least 1994 if they so desired. The Chinese Student Protection Act (CSPA), signed in 1992, further granted this cohort the option to change from temporary to permanent status during a one-year period lasting from July 1993 to July 1994. The CSPA stipulated, however, that excess immigration from the CSPA over Mainland China's numerical limit be deducted from later admissions. The timing of the CSPA partly explains the 1993 spike.

Finally, NSF surveys of graduating science and engineering doctoral students confirm the strong responses evident in the INS data. The questionnaires ask foreign-born Ph.D. students in their final year of US study about their plans after graduation. Expect stay rates increase from 60% to 90% for students from Mainland China from 1990 to 1992. Substantial increases are also apparent for Indian students. These graduating students tend to have higher flexibility in their location choices than older workers.

Our reduced-form strategy exploits differences in the extent to which nations were affected by the 1990 reform. It is inappropriate, however, to use the outcomes exhibited in Figures 8 to assign treatment and control groups directly. A proper designation of the affected source countries requires a more formal analysis of ISE responses to the legislation change. Let $\text{ISE\%}_{n,t_0}^{Adm}$ be the mean ISE arrivals from nation n divided by an approximate country-level numerical limit for employment-based workers during the 1983-1990 pre-period. The theoretical numerical limit is taken to be the 20,000 country limit multiplied by the 20% worldwide allocation given to employment-based applications (i.e., 54,000/270,000). The left-hand columns of Table 6 demonstrate that the theoretical limit works quite well. The listed scientific percentages are even larger than they initially appear since family members of employment-based admissions count towards the two quotas.

Define POST_t as a indicator variable taking the value of zero from 1983-1990 and one for 1991 and after (i.e., the 1990 Act's effective date). Regressing annual ISE admissions ($\text{ISE}_{n,t}^{Adm}$) on an interaction of $\text{ISE\%}_{n,t_0}^{Adm}$ with POST_t quantifies the immigration response of constrained countries,

$$\text{ISE}_{n,t}^{Adm} = \phi_n + \eta_t + \gamma \cdot [\text{ISE\%}_{n,t_0}^{Adm} \cdot \text{POST}_t] + \epsilon_{n,t}. \tag{5}$$

The main effect for $\text{ISE\%}_{n,t_0}^{Adm}$ is absorbed by the nation FEs ϕ_n, along with levels differences between nations in US immigration. The year FEs η_t remove aggregate changes in US permanent residency admissions and control for the main effect of POST_t.

The γ coefficient in (5) will be positive and significant if raising the two numerical limits spurred ISE immigration from previously constrained countries (i.e., high values of $\text{ISE\%}_{n,t_0}^{Adm}$).

The coefficient from this regression is 4.7 (0.2), and economies with high values of $\text{ISE}\%_{n,t_0}^{Adm}$ become the treatment group regardless of actual responses. From the waiting list and 1983-1990 flow data presented in Table 6, the treated groups are determined to be India, Mainland China, the Philippines, and Taiwan. Hong Kong's immigration status was not affected by the 1990 reform due to special circumstances, but it would have also been included in the treatment group. Despite the positive dependency for the Philippines, we focus on just Chinese and Indian ISEs as the treated group as we cannot separate Filipino ISEs from the larger Hispanic grouping.

Our reduced-form estimator thus exploits the concentrated impact of the quota changes from the 1990 Act on Chinese and Indian ISE inflows vis-a-vis other ethnicities even among SE immigration. To construct the estimator, we first assume that only the previous three years of immigration matter for an inventor pool. This design is clearly quite stark, but the very sharp surge in immigration in Figure 8 makes this assumption more reasonable for the purposes of modelling the discontinuity of the 1990 Act. We then define $\text{QUOTA}_t^{Chn,Ind}$ as the effective quota for Chinese and Indian ISEs in year t. Prior to the 1990 Act, this effective quota was the country limit of 20,000 interacted with the 20% of slots devoted to employment-based applications. After the reform, the effective quota increases to reflect both the higher country limit of 25,600 and the larger employment preference allocation of 36% (i.e., 120,120/336,000).

The reduced-form immigration estimator takes the form,

$$\text{QUOTA}_t^{Chn,Ind} = \sum_{s=1}^{5} \left(\text{QUOTA}_{t-s}^{Eff} + \text{QUOTA}_{t-s-1}^{Eff} + \text{QUOTA}_{t-s-2}^{Eff} \right), \qquad (6)$$

where the summation is over the five years included in each of our time periods. This summation allows for growing impacts of the higher quotas as the pool of Chinese and Indian ISEs increases. While the quotas are applied at the country level, the same effective quota shift is present for all Chinese and Indian ISEs subject to a multiplicative constant. This scaling is not important for our panel estimation techniques utilizing log variables. The formula (6) thus abstracts from summing across countries within the Chinese and Indian ethnicities for a simpler presentation.

To be clear, the legal change in quotas is not specific to Chinese economies and India. The quota change technically applied to all countries. The reduced-form approach centers, however, on the fact that only a few countries were constrained under the previous regime with respect to scientific immigration. By linking the quotas changes to the Chinese and Indian inflows, the design is implicitly suggesting that raising the numerical ceilings did not change the effective quotas for nations that were unconstrained by the former immigration regime (i.e., low $\text{ISE}\%_{n,t_0}^{Adm}$). Their effective quotas are held constant at the pre-reform theoretical limit.

4.2 Reduced-Form Results

Table 7 presents the reduced-form results. The design is the same format as in specification (3), and we have again taken a log of the reduced-form estimator (6). The core interaction term is the initial dependency upon Chinese and Indian inventors by technology. The first column finds a positive association between national increases in Chinese and Indian immigration quotas and invention reallocation in dependent industries compared to non-dependent industries. The elasticity in the reduced-form exercises cannot be directly compared to the least squares elasticity, but the two findings support each other qualitatively. To help interpret the coefficient, the appendix again presents a quintile-based framework similar to specification (4). The results suggest that a 10% increase in Chinese and Indian SE immigration due to the 1990 Act yielded a 1.5% greater spatial reallocation in the most dependent 20% of technologies relative to the reference group of the least dependent 40% of technologies. Similar to the earlier interactions, positive differences are found for the second and third most dependent quintiles, but these differences are not statistically significant.

The second column further compares the response among technologies dependent initially on Chinese and Indian workers with initial dependence upon other non-English inventor groups. The interaction here is between the national increase in Chinese and Indian quotas following the 1990 Act and the pre-period dependency of the technology on other non-English inventors. This design differs from the second columns of Tables 4 and 5, where national trends were ethnic-specific in the interactions; there is no longitudinal variation for the other non-English ethnicities with the reduced-form estimator (6) for unconstrained countries. The isolated effect of the Chinese and Indian ISE inflow to the initial dependency for Chinese and Indian inventors is confirmed. This test provides confidence that the identified, exogenous variation is not reflecting omitted factors.

Unlike our earlier estimations, the third column shows sensitivity of this reduced-from estimator to the inclusion of technology group by period FEs. While remaining statistically significant, the elasticity loses almost half of its economic magnitude. This greater sensitivity is due the weaker variation that exists in initial Chinese and Indian contributions by technology within each of the 36 sub-category groupings. As before, the final two columns show that the measured elasticities are somewhat reduced by excluding semiconductor or software patents, but the overall pattern of findings is quite consistent.

While the reduced-form estimator helps mitigate reverse causality concerns, its simple design does have limitations. Most noticeably, the interaction could be biased by unmodeled factors that are changing contemporaneously to the immigration reforms. To partially test this concern, we construct two placebo estimators for comparison. These placebo estimators move the effective date of the 1990 Act forward or back five years. We then test whether the placebos have greater explanatory power than the 1990 Act estimator. A substantial loss in measured reallocation due to the 1990 Act in the presence of the placebo estimators would suggest that the primary results may be reflecting unmodeled factors that were happening nearby the true reform. Columns 4 includes the placebo estimator with the effective date five years earlier (a "1985 Act"); the fifth column models the placebo "1995 Act". Incorporating these two estimators does not substantively affect the core results, and the estimated elasticity for the placebo reforms are essentially zero. This suggests that the reduced-form design is not keying in on a trend that predates or comes after the 1990 Act.[18]

5 Entrepreneurship Outcomes

<This section is to be developed from the Census Bureau's LBD database. SIC industries will be linked to patent technologies. A similar battery of tests to those above will measure whether startup entry in dependent industries reallocates faster with greater inflows. We will also study new facility expansions by existing firms.>

6 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 several high-tech sectors. This paper highlights the role that this immigration plays in promoting faster spatial reallocation of invention across US cities. While establishing a link, several key questions remain. Most importantly, we do not identify where or why the innovation is migrating across cities. Some of this movement is external to immigrants (e.g., shifting market demands, government policies), but portions of it may reflect immigrant desires for certain locations. We hope that future work can parse out the relative contributions of these factors and whether ISE inflows create path dependencies in future ISE placements. Such an accounting will allow us to say more clearly what lies behind the increasing spatial clustering of invention evident since the mid 1990s and the economic consequences.

[18] An earlier version of this paper tested the placebo design using only variation across the 36 sub-category groupings. At this level, the results are more sensitive to including the lagged estimator ("1995 Act"). The elasticity for the true estimator declines by 40% and is comparable in magnitude to the placebo. Thus, the estimator may be picking up some trends commencing after the approximate date of the 1990 Act. A likely candidate for this sensitivity is the expansion of the H-1B program. This temporary worker visa (formalized by the 1990 Act) became a very popular channel for bringing Indian and Chinese workers for SE into the US in the late 1990s. Kerr and Lincoln (2008) provide further details on the trends, which are not modelled in the reduced-form specification.

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Fig. 1: Ethnic Share of US Domestic Patents

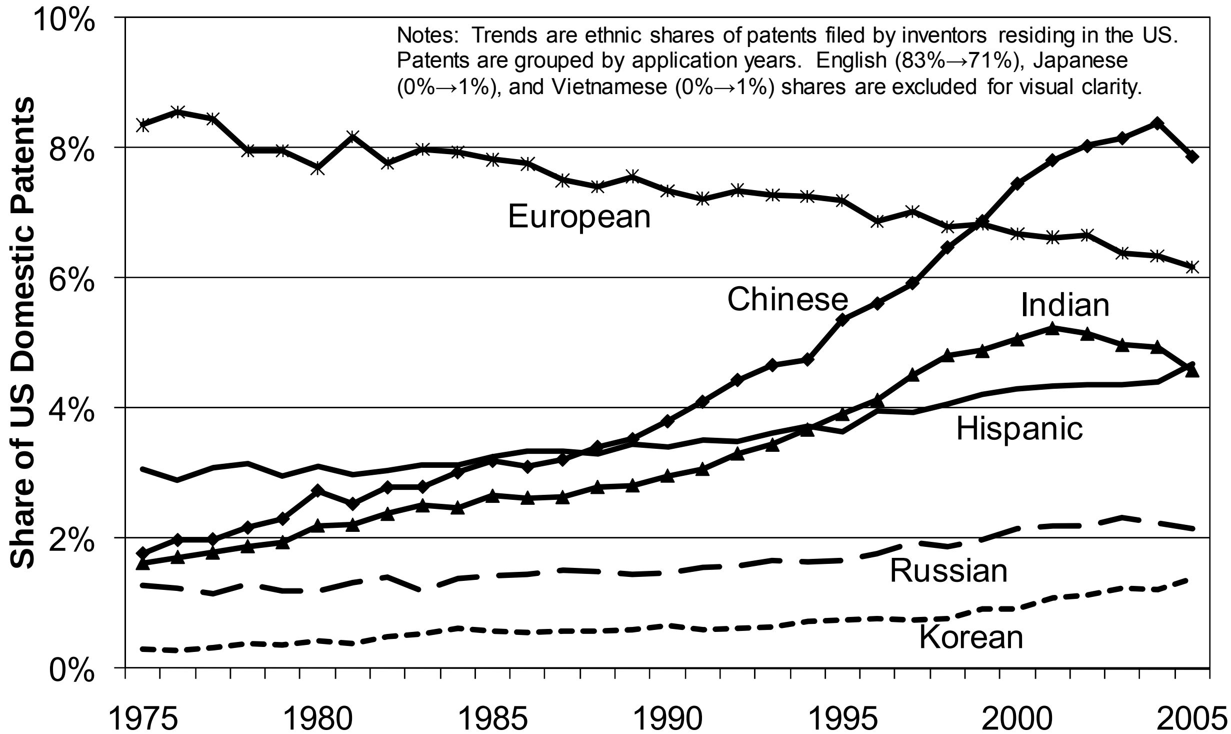

Fig. 2: non-English Share by Technology

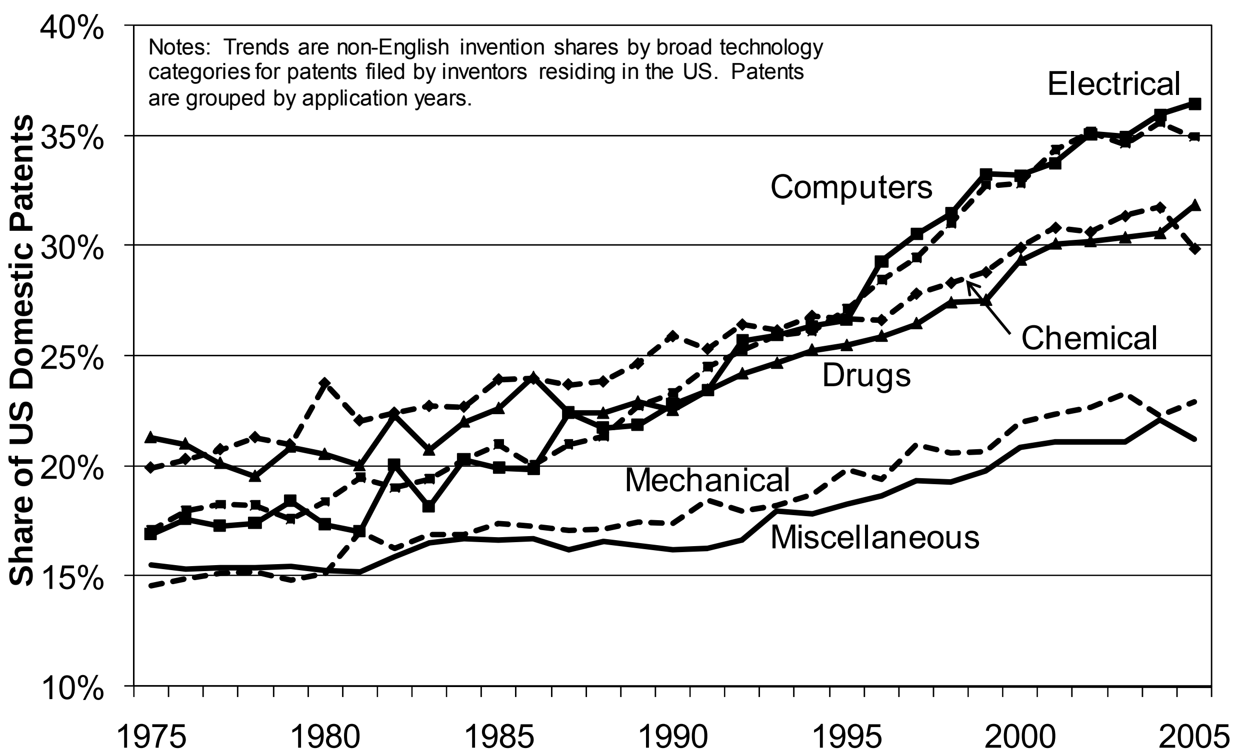

Fig. 3: Chinese Share by Technology

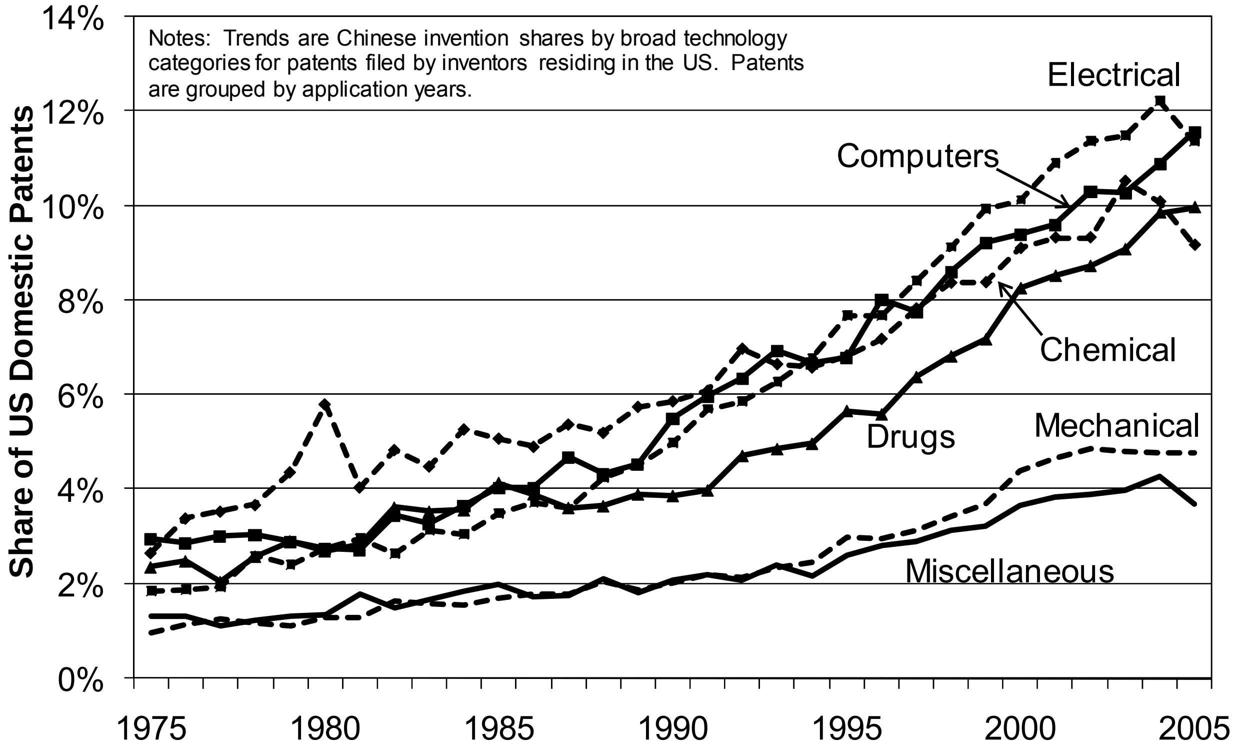

Fig. 4: Indian Share by Technology

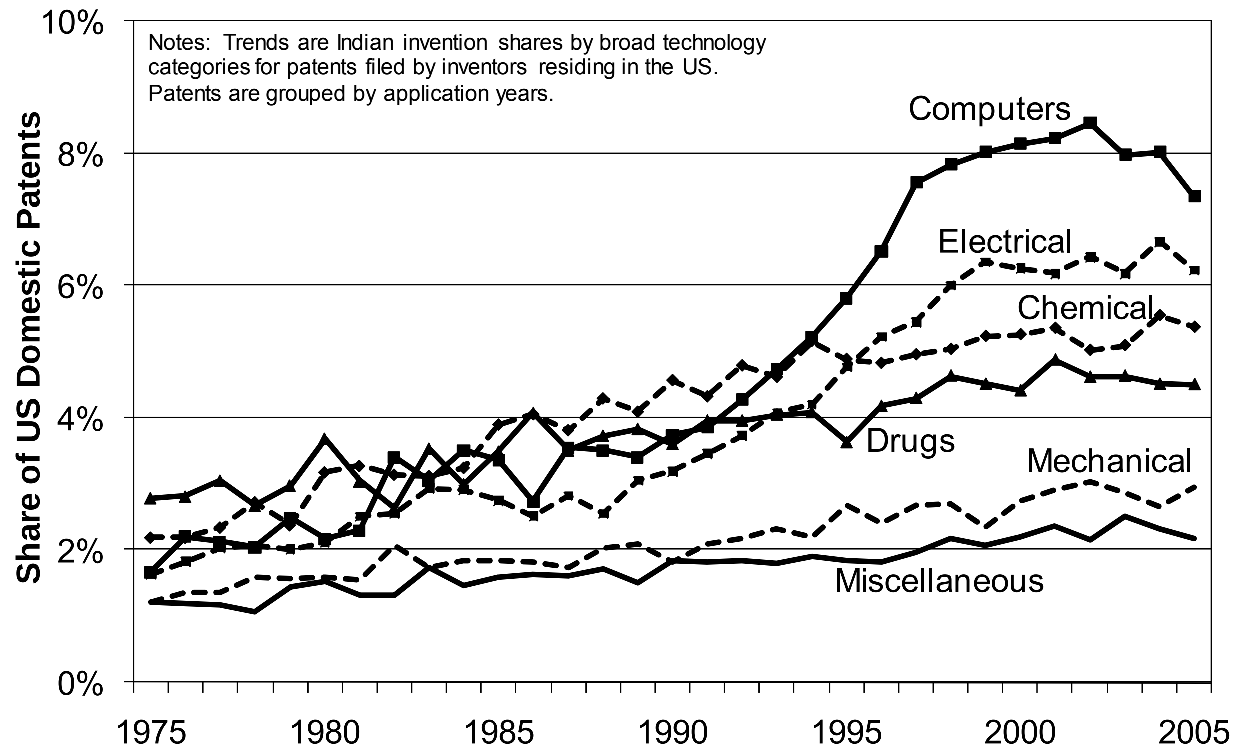

Fig. 5: HHI Concentration of US Patents

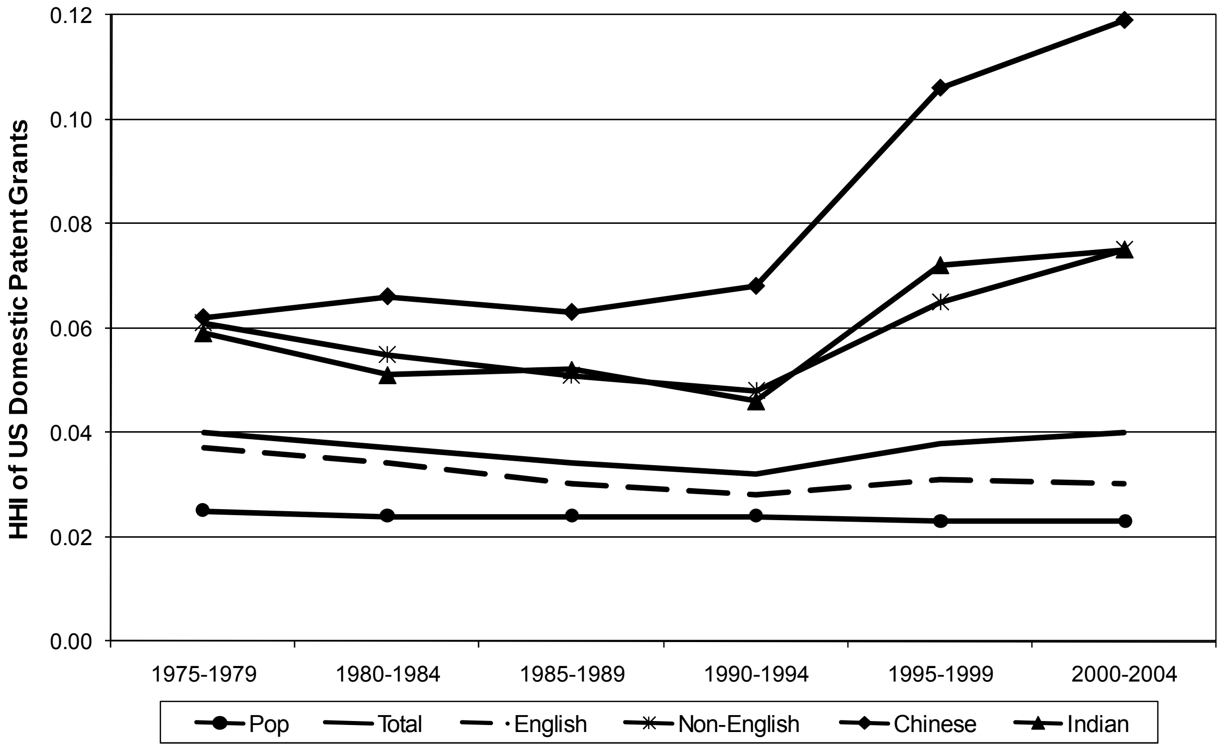

Fig. 6: Ethnic HHI, All Inventors

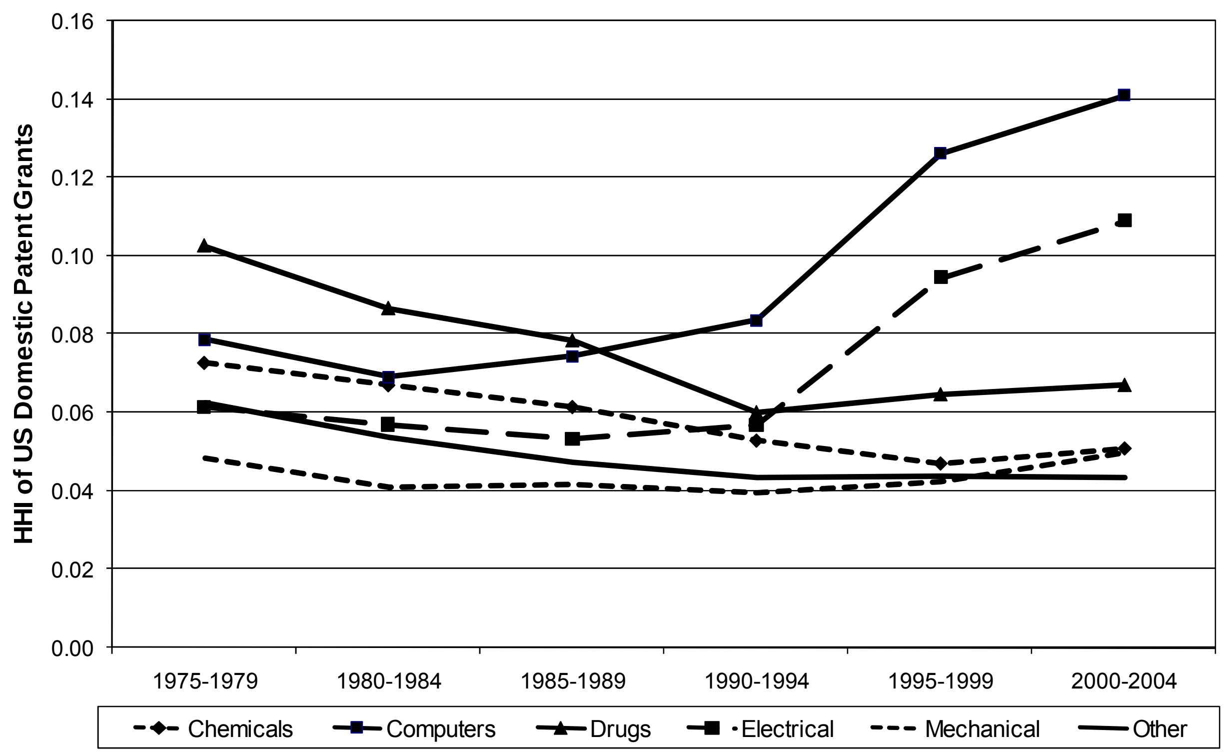

Fig. 7: Ethnic HHI, University & Government

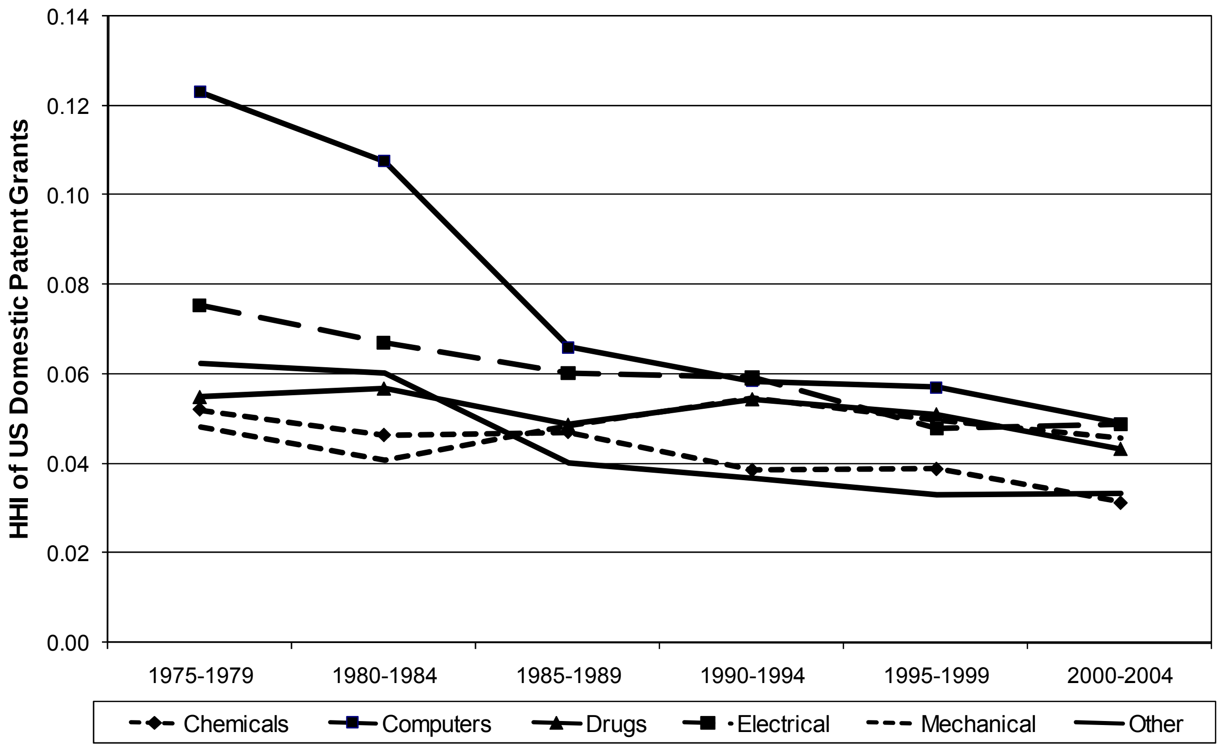

Figure 8: Science & Engineering Immigration

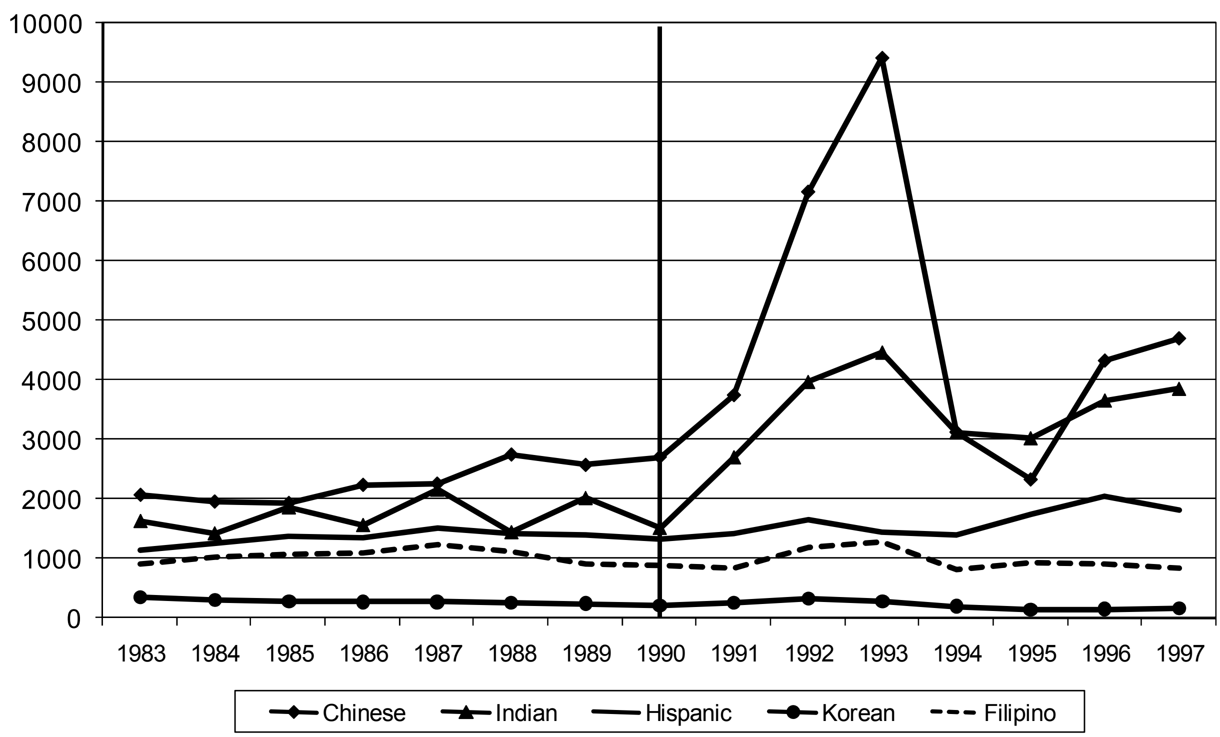

Table 1: Descriptive Statistics for Inventors Residing in US

	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. Immigrant Scientist and Engineer Shares Estimated from 1990 US Census Records								
Bachelor's 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: Shifting Ethnic Inventor Contributions Among Top Patenting Cities

	City Rank			English Inventor Share of City			Chinese and Indian Inventor Share of City			Other Ethnicity Inventor Share of City		
	1975-1984	1995-2004	Rank Change	1975-1984	1995-2004	Share Change	1975-1984	1995-2004	Share Change	1975-1984	1995-2004	Share Change
San Francisco, CA	5	1	+4	76%	55%	-21%	9%	26%	18%	15%	19%	3%
New York, NY	1	2	-1	74%	60%	-14%	8%	19%	12%	19%	21%	2%
Los Angeles, CA	4	3	+1	80%	64%	-16%	5%	16%	11%	15%	20%	5%
Boston, MA	6	4	+2	81%	71%	-10%	5%	11%	6%	14%	18%	4%
Chicago, IL	2	5	-3	79%	74%	-6%	5%	11%	6%	16%	16%	-1%
Detroit, MI	7	6	+1	81%	74%	-7%	6%	11%	6%	14%	15%	1%
Minneap.-St. Paul, MN	11	7	+4	84%	79%	-5%	3%	8%	5%	12%	12%	0%
Philadelphia, PA	3	8	-5	78%	70%	-7%	6%	14%	7%	16%	16%	0%
Dallas-Fort Worth, TX	13	9	+4	87%	69%	-18%	5%	18%	13%	8%	13%	5%
Austin, TX	36	10	+26	77%	72%	-6%	4%	15%	11%	18%	14%	-5%
San Diego, CA	26	11	+15	78%	66%	-13%	5%	15%	10%	16%	19%	3%
Seattle, WA	21	12	+9	84%	74%	-10%	4%	13%	9%	12%	14%	1%
Rochester, NY	12	13	-1	80%	76%	-4%	7%	13%	6%	13%	11%	-2%
Houston, TX	9	14	-5	85%	74%	-11%	4%	12%	7%	11%	14%	4%
Boise City, ID	161	15	+146	96%	72%	-24%	2%	19%	16%	2%	9%	7%
Cleveland, OH	8	21	-13	81%	78%	-3%	5%	9%	4%	14%	13%	-1%
Cincinnati, OH	15	22	-7	83%	81%	-2%	4%	7%	4%	14%	12%	-2%
Albany-Sch.-Troy, NY	14	25	-11	78%	68%	-10%	8%	16%	9%	14%	16%	1%
Pittsburgh, PA	10	26	-16	80%	78%	-2%	5%	9%	4%	15%	13%	-2%
Top Cities Overall				81.1%	71.3%	-9.8%	5.2%	13.7%	8.5%	13.6%	14.9%	1.3%
- Those Improving Rank				82.4%	69.7%	-12.7%	4.9%	15.1%	10.2%	12.8%	15.2%	2.5%
- Those Losing Rank				79.7%	73.2%	-6.5%	5.7%	12.1%	6.5%	14.6%	14.7%	0.0%

Notes: See Table 1. Listed cities include the top 15 patenting cities in 1975-1984 and 1995-2004. Ethnic shares are relative to each city's invention in the indicated period.

Table 3: Shifting Ethnic Inventor Contributions Among All Cities

	English Inventor Share of City			Chinese and Indian Inventor Share of City			Other Ethnicity Inventor Share of City		
	1975-1984	1995-2004	Share Change	1975-1984	1995-2004	Share Change	1975-1984	1995-2004	Share Change
				A. Industry Patenting					
All 281 Cities	87.0%	82.1%	-4.9%	3.0%	6.6%	3.6%	10.0%	11.3%	1.3%
- Above Median Growth	87.9%	80.7%	-7.2%	2.8%	7.4%	4.6%	9.3%	11.9%	2.6%
- Below Median Growth	86.0%	83.5%	-2.5%	3.3%	5.7%	2.5%	10.7%	10.7%	0.0%
				B. University and Government Patenting					
All 281 Cities	87.3%	84.1%	-3.2%	2.0%	4.6%	2.7%	10.7%	11.3%	0.6%
- Above Median Growth	87.0%	82.7%	-4.4%	2.5%	5.2%	2.8%	10.5%	12.1%	1.6%
- Below Median Growth	87.6%	85.6%	-2.0%	1.4%	4.0%	2.5%	11.0%	10.4%	-0.5%

Notes: See Table 1.

Table 4: OLS Estimations of US Ethnic Inventors and the Spatial Reallocation of Invention

	Base OLS Estimation	Separating Ethnicities	Technology Group x Period FE	Above Med. Growth Interaction	Increasing Concentration Interaction	Excluding Semi-Conductors	Excluding Software Patents
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is Log Spatial Reallocation of Invention across US Cities by Technology-Period Estimations include Technology and Period Fixed Effects						
Log non-English Invention	0.110		0.112	0.041	0.099	0.102	0.102
by Technology-Year	(0.018)		(0.019)	(0.026)	(0.023)	(0.019)	(0.021)
Log non-English Invention x				0.067			
Above-Median Invention Growth				(0.024)			
Log non-English Invention x					0.013		
Increasing Spatial Concentration					(0.024)		
Log Chinese & Indian Invention		0.042					
by Technology-Year		(0.014)					
Log Other Asian Invention		0.009					
by Technology-Year		(0.009)					
Log European & Russian Invention		0.036					
by Technology-Year		(0.023)					
Log Hispanic Invention		0.021					
by Technology-Year		(0.015)					
Observations	1430	1413	1430	1430	1430	1415	1385

Notes: Estimation quantify the OLS relationship between growth in ethnic invention and spatial shifts in invention across US cities. Periods are constructed as five-year blocks from 1980-1984 to 2000-2004. Technologies are classified at the patent class level of the USPTO system. Technologies must have 100 US domestic patents in each time period to be included, resulting in 286 technologies. The dependent variable is calculated as the log sum of reallocations across 281 cities, where reallocation is the absolute change in a city's share of the technology's patents from the previous period divided by the average city share for the two periods. Changes for 1980-1984 are calculated using data extending to 1975-1979. The core regressor is the log ethnic patenting in the technology by period. Regressions include technology and period FEs. Regressions are weighted by the mean log patenting of technologies and report standard errors clustered cross-sectionally by technology.

Column 1 presents the base regression. Column 2 separates non-English invention into ethnic groupings. Other Asian Invention includes Japanese, Korean, and Vietnamese invention. Column 3 includes technology group x period FE, where technologies are grouped by 36 USPTO sub-categories. Column 4 interacts the non-English invention regressor with an indicator variable for technologies exhibiting above-median invention growth during the sample period. Column 5 interacts the non-English invention regressor with an indicator variable for technologies exhibiting growing spatial concentration during the sample period. Column 7 drops semiconductor patents (subcategory 46). Column 8 drops software patents as described in the text.

Table 5: Interactions of National Ethnic Invention Trends with Initial Technology Dependency

	Base Interaction Estimation	Separating Ethnicities	Technology Group x Period FE	Above Med. Growth Interaction	Increasing Concentration Interaction	Excluding Semi-Conductors	Excluding Software Patents
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is Log Spatial Reallocation of Invention across US Cities by Technology-Period Estimations include Technology and Period Fixed Effects						
Log US non-English Invention x Log 1975-1979 Tech. Dependency on non-English Inventors	0.170 (0.054)		0.151 (0.063)	0.128 (0.050)	0.159 (0.049)	0.117 (0.044)	0.173 (0.055)
Log non-English Patenting x Above-Median Patenting Growth				0.029 (0.007)			
Log non-English Patenting x Increasing Spatial Concentration					0.017 (0.009)		
Log US Chinese & Indian Invention x Log 1975-1979 Tech. Dependency on Chinese & Indian Inventors		0.045 (0.015)					
Log US Other Asian Invention x Log 1975-1979 Tech. Dependency on Other Asian Inventors		0.016 (0.013)					
Log US European & Russian Invention x Log 1975-1979 Tech. Dependency on European & Russian Inventors		-0.049 (0.067)					
Log US Hispanic Invention x Log 1975-1979 Tech. Dependency on Hispanic Inventors		-0.027 (0.030)					
Observations	1430	1375	1430	1430	1430	1415	1385

Notes: See Table 4. Estimations quantify the relationships among national immigrant inventor trends, the initial dependency on ethnic inventors for each technology, and the subsequent spatial reallocation of invention. The core regressor is the interaction of the log non-English invention aggregated across cities in each period with each technology's initial dependency on non-English inventors in 1975-1979. Main effects are absorbed into the technology and period FEs. Other ethnic interactions are similarly defined with initial dependencies being ethnic specific.

Table 6: Reduced-Form Preliminaries for Immigration Act of 1990

	1983-1990 Occupation Admissions As A Percentage of Theoretical Employment Quota for Country				Employment Visa Waiting List January 1992		
	Scientists	Business	Total		High-Skill	Skilled	Low-Skill
Hong Kong	20.5%	15.6%	102.6%	The Philippines	6795	9550	5995
India	18.5%	5.7%	83.3%	Mainland China	3266	1942	2976
Taiwan	18.2%	10.8%	102.0%	India	3132	1156	1131
United Kingdom	11.7%	13.9%	103.7%	Taiwan	2065	2411	1613
Iran	8.4%	4.5%	54.1%	Nigeria	1854	166	298
Mainland China	6.5%	5.3%	57.1%	Great Britain	1841	2521	714
The Philippines	4.6%	8.4%	96.4%	Canada	1587	2107	191
Canada	3.8%	9.5%	67.7%	Hong Kong	811	1350	885
South Korea	2.2%	5.0%	69.0%	Iran	804	1536	927
Pakistan	1.8%	1.4%	13.0%	Japan	787	1634	800
Israel	1.7%	1.6%	24.5%	South Korea	539	1656	5466
World Average	0.8%	0.8%	8.8%	Total	50,003	32,452	87,806

Notes: The left-hand panel documents employment-based admissions to US for 1983-1990 as a share of the theoretical country limit descending from the US quotas structure for permanent residency immigration prior to the 1990 Act. Occupational percentages for scientists and business are even stronger than they appear as family members are counted towards the quotas. The right-hand panel documents INS waiting list records close to the October 1991 effective date of the 1990 Act.

Table 7: Reduced-Form Estimations from Immigration Act of 1990

	Base Quotas RF Estimation	Comparison to Other Ethnicities	Technology Group x Period FE	Forward Placebo Estimator	Lagged Placebo Estimator	Excluding Semi-Conductors	Excluding Software Patents
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is Log Spatial Reallocation of Invention across US Cities by Technology-Period Estimations include Technology and Period Fixed Effects						
Log RF Imm. Quotas Estimator x Log 1975-1979 Tech. Dependency on Chinese & Indian Inventors	0.094 (0.026)	0.096 (0.027)	0.054 (0.034)	0.075 (0.031)	0.083 (0.028)	0.073 (0.023)	0.088 (0.027)
Log RF Imm. Quotas Estimator x Log 1975-1979 Tech. Dependency on Other non-English Inventors		-0.019 (0.078)					
Placebo Estimator Five Years Earlier x Log 1975-1979 Tech. Dependency on Chinese & Indian Inventors				0.025 (0.029)			
Placebo Estimator Five Years Later x Log 1975-1979 Tech. Dependency on Chinese & Indian Inventors					0.015 (0.028)		
Observations	1430	1430	1430	1430	1430	1415	1385

Notes: See Tables 4-6. Estimations quantify the relationships among national immigration quotas changes following the Immigration Act of 1990, the initial dependency on Chinese and Indian inventors for each technology, and the subsequent spatial reallocation of invention across US cities. The core regressor is expected Chinese and Indian invention nationally due to immigration quotas altered by the 1990 Act interacted with each technology's initial dependency on Chinese and Indian inventors in 1975-1979. Main effects are absorbed into the technology and period fixed effects. Columns 4 and 5 include placebo estimators that move the effective date of the 1990 Act forward or back five years.

App. Table: Ethnic Inventor Contributions by City

	Total Invention Share				non-English Ethnic Invention Share				Chinese and Indian Invention 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%	1.5%	0.3%	0.7%	1.0%	1.1%	0.3%	0.7%	1.0%	1.2%
Austin, TX	0.4%	0.9%	1.8%	2.0%	0.5%	1.2%	1.9%	2.0%	0.4%	1.6%	2.3%	2.3%
Baltimore, MD	0.8%	0.8%	0.7%	0.7%	0.7%	0.7%	0.6%	0.5%	0.4%	0.5%	0.6%	0.5%
Boston, MA	3.6%	3.8%	3.9%	4.6%	3.9%	4.2%	4.1%	4.8%	4.0%	4.0%	3.6%	4.3%
Buffalo, NY	0.6%	0.5%	0.4%	0.3%	0.8%	0.6%	0.4%	0.3%	1.1%	0.7%	0.4%	0.3%
Charlotte, NC	0.3%	0.3%	0.3%	0.3%	0.2%	0.2%	0.2%	0.2%	0.1%	0.2%	0.1%	0.2%
Chicago, IL	6.0%	4.6%	3.5%	3.2%	6.9%	5.0%	3.5%	3.0%	5.6%	3.9%	2.9%	2.8%
Cincinnati, OH	1.0%	1.1%	1.0%	1.0%	0.9%	0.9%	0.7%	0.7%	0.7%	1.0%	0.6%	0.6%
Cleveland, OH	2.3%	1.7%	1.3%	1.1%	2.5%	1.5%	1.0%	0.8%	2.5%	1.4%	0.9%	0.6%
Columbus, OH	0.7%	0.5%	0.5%	0.4%	0.6%	0.6%	0.4%	0.3%	0.8%	0.7%	0.3%	0.3%
Dallas-Fort Worth, TX	1.6%	2.0%	2.3%	2.1%	1.1%	1.9%	2.3%	2.2%	1.5%	2.4%	2.9%	2.8%
Denver, CO	1.0%	1.2%	1.3%	1.3%	0.8%	1.0%	0.9%	0.8%	0.8%	1.0%	0.6%	0.5%
Detroit, MI	3.1%	3.3%	2.9%	2.8%	3.1%	3.1%	2.6%	2.6%	3.2%	2.8%	2.5%	2.5%
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%	0.6%	1.0%	0.8%	0.5%	0.5%	0.8%	0.6%	0.3%	0.4%
Houston, TX	2.3%	2.5%	1.9%	2.0%	1.8%	2.3%	1.8%	1.9%	2.2%	2.8%	1.8%	1.9%
Indianapolis, IN	0.8%	0.7%	0.7%	0.5%	0.6%	0.4%	0.4%	0.3%	0.7%	0.5%	0.4%	0.3%
Jacksonville, NC	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
Kansas City, MO	0.4%	0.3%	0.4%	0.3%	0.2%	0.2%	0.2%	0.2%	0.2%	0.1%	0.2%	0.2%
Las Vegas, NV	0.1%	0.1%	0.2%	0.3%	0.1%	0.1%	0.2%	0.2%	0.0%	0.1%	0.1%	0.1%
Los Angeles, CA	6.6%	6.1%	6.0%	5.7%	7.2%	7.2%	7.9%	7.3%	6.7%	6.9%	7.5%	7.0%
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%	0.7%	1.0%	1.3%	1.0%	0.9%	0.5%	0.6%	0.5%	0.4%
Milwaukee, WI	1.0%	0.9%	0.8%	0.7%	0.8%	0.8%	0.6%	0.5%	0.5%	0.4%	0.5%	0.4%
Minneap.-St. Paul, MN	1.9%	2.4%	2.7%	2.8%	1.6%	2.0%	2.0%	2.0%	1.5%	1.7%	1.7%	1.8%

App. Table: Ethnic Inventor Contributions by City, continued

	Total Invention Share				non-English Ethnic Invention Share				Chinese and Indian Invention 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%	0.1%	0.1%	0.1%	0.1%
New Orleans, LA	0.3%	0.2%	0.2%	0.1%	0.3%	0.3%	0.1%	0.1%	0.2%	0.2%	0.0%	0.0%
New York, NY	11.5%	8.9%	7.3%	6.9%	16.6%	13.1%	10.1%	8.9%	16.6%	13.3%	9.7%	9.0%
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%	0.1%
Orlando, FL	0.2%	0.3%	0.3%	0.3%	0.1%	0.2%	0.3%	0.3%	0.1%	0.2%	0.3%	0.3%
Philadelphia, PA	4.6%	4.0%	2.7%	2.8%	5.6%	4.9%	2.8%	2.9%	6.2%	5.8%	2.8%	3.0%
Phoenix, AZ	1.0%	1.2%	1.4%	1.3%	0.6%	1.1%	1.3%	1.2%	0.4%	1.0%	1.4%	1.3%
Pittsburgh, PA	2.0%	1.3%	0.8%	0.7%	2.2%	1.4%	0.6%	0.5%	2.2%	1.3%	0.5%	0.5%
Portland, OR	0.5%	0.8%	1.4%	1.6%	0.3%	0.6%	1.4%	1.6%	0.2%	0.6%	1.7%	2.0%
Providence, RI	0.3%	0.3%	0.3%	0.2%	0.3%	0.4%	0.3%	0.2%	0.2%	0.3%	0.2%	0.2%
Raleigh-Durham, NC	0.3%	0.6%	1.1%	1.5%	0.3%	0.6%	1.0%	1.3%	0.3%	0.8%	1.0%	1.2%
Richmond, VA	0.3%	0.3%	0.2%	0.2%	0.3%	0.3%	0.2%	0.2%	0.3%	0.4%	0.2%	0.2%
Sacramento, CA	0.2%	0.4%	0.5%	0.5%	0.2%	0.4%	0.5%	0.5%	0.2%	0.3%	0.5%	0.5%
Salt Lake City, UT	0.4%	0.5%	0.6%	0.6%	0.2%	0.4%	0.3%	0.3%	0.2%	0.3%	0.3%	0.3%
San Antonio, TX	0.1%	0.2%	0.2%	0.2%	0.1%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%
San Diego, CA	1.1%	1.6%	2.2%	2.8%	1.1%	1.6%	2.6%	3.6%	0.8%	1.4%	2.4%	3.9%
San Francisco, CA	4.8%	6.6%	12.1%	13.2%	6.2%	9.3%	19.3%	19.9%	8.4%	13.0%	25.4%	24.0%
Seattle, WA	0.9%	1.3%	1.9%	3.4%	0.8%	1.1%	1.8%	3.5%	0.6%	1.0%	1.8%	3.7%
St. Louis, MO	1.0%	0.9%	0.8%	0.8%	0.9%	0.8%	0.8%	0.7%	1.0%	0.8%	0.4%	0.4%
Tallahassee, FL	0.4%	0.5%	0.4%	0.4%	0.3%	0.4%	0.3%	0.3%	0.2%	0.2%	0.2%	0.2%
Washington, DC	1.5%	1.5%	1.4%	1.6%	1.6%	1.6%	1.5%	1.7%	1.6%	1.7%	1.5%	1.7%
West Palm Beach, FL	0.3%	0.5%	0.4%	0.4%	0.3%	0.5%	0.4%	0.4%	0.3%	0.3%	0.2%	0.2%
Other 234 Major Cities	21.8%	22.3%	20.7%	18.4%	18.1%	18.1%	15.6%	13.6%	19.7%	18.2%	14.6%	12.7%
Not in a Major City	9.0%	8.2%	6.6%	6.2%	6.3%	5.4%	3.7%	4.1%	5.2%	3.8%	2.5%	2.7%

Notes: See Table 1. The first three columns of each grouping are for granted patents. The fourth column, marked with (A), is for published patent applications.

App. Table: Quintiles-Based Estimations for Tables 5 and 7

	Base Interaction Estimation	Indicator Variable Estimation		Base Quotas RF Estimation	Indicator Variable Estimation
	(1)	(2)		(3)	(4)
Dependent Variable is Log Spatial Reallocation of Invention across US Cities by Technology-Period Estimations include Technology and Period Fixed Effects					
Log US non-English Invention x Log 1975-1979 Tech. Dependency on non-English Inventors	0.170 (0.054)		Log RF Imm. Quotas Estimator x Log 1975-1979 Tech. Dependency on Chinese & Indian Inventors	0.094 (0.026)	
Log US non-English Invention x 3rd Most Dependent Quintile		0.012 (0.029)	Log RF Imm. Quotas Estimator x 3rd Most Dependent Quintile		0.044 (0.037)
Log US non-English Invention x 2nd Most Dependent Quintile		0.030 (0.038)	Log RF Imm. Quotas Estimator x 2nd Most Dependent Quintile		0.065 (0.052)
Log US non-English Invention x Most Dependent Quintile		0.096 (0.033)	Log RF Imm. Quotas Estimator x Most Dependent Quintile		0.156 (0.042)
Observations	1430	1430	Observations	1430	1430

Notes: See Tables 5 and 7. Quintile specifications model indicator variables for quintiles of initial dependency interacted with national invention trends. The reference category is the two least dependent quintiles.