NBER WORKING PAPER SERIES

BREAKTHROUGH INVENTIONS AND MIGRATING CLUSTERS OF INNOVATION

William R. Kerr

Working Paper 15443
http://www.nber.org/papers/w15443

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2009

Comments are appreciated and can be sent to wkerr@hbs.edu. I am grateful to Ajay Agrawal, Megan MacGarvie, Ed Glaeser, Stuart Rosenthal, Will Strange, and seminar participants at Kauffman Foundation Cities and Entrepreneurship Conference, NBER Productivity, and UBC Sauder for feedback on this work. 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. A previous version of this paper was titled "Immigrants and Spatial Adjustments in US Invention." The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

Breakthrough Inventions and Migrating Clusters of Innovation
William R. Kerr
NBER Working Paper No. 15443
October 2009
JEL No. F2,J4,J6,O3,O4,R1,R3

ABSTRACT

We investigate the speed at which clusters of invention for a technology migrate spatially following breakthrough inventions. We identify breakthrough inventions as the top one percent of US inventions for a technology during 1975-1984 in terms of subsequent citations. Patenting growth is significantly higher in cities and technologies where breakthrough inventions occur after 1984 relative to peer locations that do not experience breakthrough inventions. This growth differential in turn depends on the mobility of the technology's labor force, which we model through the extent that technologies depend upon immigrant scientists and engineers. Spatial adjustments are faster for technologies that depend heavily on immigrant inventors. The results qualitatively confirm the mechanism of industry migration proposed in models like Duranton (2007).

William R. Kerr
Harvard Business School
Rock Center 212
Soldiers Field
Boston, MA 02163
and NBER
wkerr@hbs.edu

1 Introduction

The spatial location of invention can shift substantially over a short period of time. The San Francisco Bay Area grew from 5% of US domestic patents in 1975-1984 to over 12% in 1995-2004, while the share for New York City declined from 12% to 7%. Smaller cities like Austin, TX, and Boise City, ID, seem to have become clusters of innovation overnight. While the correlation in population levels of US cities between 1975-1989 and 1990-2004 is 0.99, the correlation for city patenting levels is significantly weaker at 0.88. This correlation further declines to 0.64 when looking at the spatial patenting distribution within 36 basic technology groups.

Despite the prevalence of these movements, we know very little about what drives spatial adjustments in US invention, the speed at which these reallocations occur, and their economic consequences. In this paper, we investigate whether breakthrough inventions draw subsequent research efforts for a technology to a local area. A recent theoretical model by Duranton (2007) describes the spatial evolution of cities and industries through the reallocation of production across cities following discrete technological advances in locations outside of the industry's current core. Centers of innovation are dictated by where frontier inventions occur, and production follows the location of invention to achieve agglomeration economies. While this model fits the distribution of cities and industries well in several countries (e.g., Duranton 2007, Findeisen and Südekum 2008), only anecdotal evidence has been offered that the measured industry-level churning across cities is due to technological advances that are spatially distant from existing clusters.

We investigate this missing link by comparing the growth of patenting in cities where breakthrough patents occurred to peer cities where they did not or were relatively scarce. We identify by technology the top one percent of US patents during the 1975-1984 period in terms of subsequent citations, which we refer to as breakthrough patents. Our analysis compares the technology-level growth in patenting in cities where these breakthrough patents occurred relative to similar cities also innovating in the technology in question. We do find evidence of localized patent growth after breakthrough inventions. For example, looking just among the ten largest patenting cities for a technology during 1975-1984, a one standard deviation increase in the relative presence of breakthrough patents results in a 20% greater patenting growth for 1990-2004.

To further characterize this relationship, we examine whether the spatial reallocation occurs faster if the technology has a more spatially mobile workforce. We proxy the latter through the extent to which the technology depends upon immigrant scientists and engineers (SEs). Immigrants are very important for US invention, representing 24% and 47% of the US SE workforce with bachelor's and doctorate educations in the 2000 Census of Populations, 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 SE workforce has come through immigration (e.g., Kerr and Lincoln 2008). Using Census records, we show that immigrant SEs are more mobile within the US than their domestic counterparts. Second, and more important, the flexibility of new immigrants in their initial location decisions provides an important margin for adjusting the geography of innovation. Immigrants over the past five years represent 6% of the SE workforce in the 2000 Census but 25% of the net moves.

We show that this greater flexibility and growing immigrant contributions result in technology migration being faster across clusters for technologies that depend heavily on immigrant SEs. As a final step, we confirm that immigrants speed the spatial reallocation of invention through an analysis of an exogenous surge in SE immigration following the Immigration Act of 1990. This inflow promoted faster spatial reallocation in technologies that were dependent upon these workers to cities with breakthrough technologies. This effect was particularly strong in the semiconductor industry.[1]

This study relates to an extensive literature on agglomeration and local innovation. The local nature of knowledge flows is frequently noted, making the spatial clustering of invention and related entrepreneurship important.[2] Recent research, like Duranton (2007), has begun to characterize the extent to which industries migrate across cities and the underlying causes. Empirical work further documents that high-tech industries relocate across US cities and states particularly quickly.[3] This study complements this literature but also describes an under-appreciated aspect. Major technology advances require extensive refinement and follow-on R&D to transform breakthrough concepts into realized products. Developing this SE labor force itself takes time, well before production would migrate. Our analysis of migration speed and the composition of the technology's SE workforce also provides a partial explanation for why technology-intensive industries migrate faster, although clearly other factors may be important, too (e.g., less dependency upon natural resources that are spatially fixed).

Second, understanding these trends is important for labor economics. It is well documented that immigrants have a substantial impact on US innovation. Most research on this phenom-

[1] Saxenian (1994, 1999) anecdotally links these phenomena for semiconductors when she reports, "When local technologists claim that 'Silicon Valley is built on ICs' they refer not to the integrated circuit but to Indian and Chinese engineers." This growth of the semiconductor industry in Silicon Valley represented a substantial migration from the Route 128 corridor outside of Boston.

[2] For example, Arzaghi and Henderson (2008), Carlino et al. (2007), Carlino and Hunt (2007), Delgado et al. (2008, 2009), Ellison et al. (2009), Glaeser and Kerr (2009), Jacobs (1970), Jaffe et al. (1993), Marshall (1920), Rosenthal and Strange (2003), Thompson (2006), and Thompson and Fox-Kean (2005). Within this volume, this phenomena closely relates to the company towns described by Agrawal et al. (this issue) and the mobility of technical workers analyzed by Dahl and Sorenson (this issue). Our work also relates to cluster formation analyzed by Glaeser et al. (this issue) and Klepper (this issue).

[3] For example, Arzaghi and Davis (2005), Beardsell and Henderson (1999), Black and Henderson (1999), and Wallace and Walls (2004). Broader studies of industrial locations across cities include Dumais et al. (2002), Glaeser et al. (1992), Henderson et al. (1995), and Simon (2004).

ena focuses on determining the size of these contributions and the potential crowding-in or crowding-out of natives.[4] This paper is a step towards understanding how immigrants influence spatial patterns of US 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 is true for SE occupations and spillovers into other occupations. The speed at which productive matches are realized would similarly need to be considered. Future research uniting immigrants, shifts in industrial spatial structures, and native outcomes is particularly warranted.[5]

The next section describes the patent data we employ and its preparation. Section 3 provides cross-sectional growth estimations of technology migration patterns into cities experiencing breakthrough technologies. Section 4 further characterizes the role of immigrants in spatial adjustments of US invention. The final section concludes.

2 Patterns of US Invention 1975-2004

We employ 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). The data are extensive, with 8 million inventors associated with 4.5 million granted patents during this period. 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.

This section first describes how we identify breakthrough inventions from these data. We then describe how we measure the reliance of technologies on immigrant SEs through assigning probable inventor ethnicities for each patent. The section closes with tabulations of recent patterns of innovation in prominent US cities. Cities with high patent growth after 1990 are both 1) home to more breakthrough technologies in 1975-1984 and 2) are contemporaneously experiencing large increases in immigrant invention.

[4]For example, Borjas (2003, 2004), Card (2001), Friedberg and Hunt (1995), Hunt (2009), Hunt and Gauthier-Loiselle (2008), Kerr and Lincoln (2008), Matloff (2003), and Peri (2007). Borjas (1994) and Kerr and Kerr (2008) survey the immigration literatures, and Saxenian (1999), Stephan and Levin (2001), and Wadhwa et al. (2007) provide additional descriptions of high-skilled SE immigration.

[5]This work also relates to studies in urban and labor economics of worker choices over cities. It most directly connects to Bartel's (1989) and Borjas's (2001) emphasis on the role of immigrants for general spatial adjustments to US employment. Greenwood (1997) surveys the internal migration literature. Our work also complements analyses of business and household location decisions like Chen and Rosenthal (2008), Gabriel and Rosenthal (2004), and Holmes (1998).

2.1 Identifying Breakthrough Inventions

Identifying breakthrough inventions is quite challenging. Our approach is to define breakthrough patents for 1975-1984 by the number of citations that each patent subsequently received. Trajtenberg (1990) and related studies find that citations are a reasonable proxy for the value of a patent. We note, however, that this proxy contains measurement error. Similar to academic papers, we are reluctant to use citation counts to rank order all patents within a technology. We thus take the top one percent of patents for each technology as our group of breakthrough patents. To maintain a workable sample size, we principally define technologies through the 36 sub-categories of the USPTO classification scheme (e.g., "Optics", "Biotechnology", and "Nuclear & X-rays"). In robustness checks, we consider different thresholds for identifying breakthrough patents and also narrower technology divisions. The average threshold across sub-categories is 42 citations, ranging from 26 to 87. Across all patents, the median and mean citation counts are 3 and 4.8.

We next assign patents to cities using inventor locations. Our initial mapping includes 280 Metropolitan Statistical Areas. We only employ patents with inventors who are residing in the US at the time of their patent application. 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 high citation patents and all city names with more than 100 patents are identified. Our final sample is restricted to 240 cities that could be consistently matched to the 1990 Census of Populations. This excludes some smaller cities, but affords a consistent sample when including covariates in the regression analyses. The appendix lists major US cities and their shares of US invention.[6,7]

While theoretic models like Duranton (2007) describe a technology frontier where one city holds the state-of-the-art patent per technology, the major advances for many technologies will occur in several cities simultaneously. This is particularly true for a large country like the US with multiple industrial centers. We thus do not designate a single frontier city for a technology, but instead model the relative number of breakthrough inventions that occurred in locations. Formally, our primary metric for a city-technology pair is the city's share of breakthrough patents

[6] The unpublished appendix is available at http://www.people.hbs.edu/wkerr/.

[7] 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.

for a technology j divided by the city's share of all patents for the technology:

$$\text{Breakthrough Ratio}_{c,j} \equiv \frac{\text{High Citation}\%_{c,j}^{1975-1984}}{\text{Total Patent}\%_{c,j}^{1975-1984}}. \quad (1)$$

Both percentages sum to 100% across cities within each technology. High values indicate that a city was disproportionately the center of new breakthrough innovations for a technology. A ratio of one indicates that the city's share of breakthrough patents was exactly in proportion to the city's existing base of invention.

To focus on meaningful data, we restrict the sample to city-technology observations with at least ten patents during 1975-1984. The mean ratio across all of these observations is 0.84; the average ratio will generally not be equal to one with the ratio formulation. Of course, most cities do not have ten patents in every technology in the pre-period. A total of 237 cities have at least one technology represented. The unweighted average ratio at the city level is 0.66. This lower mean value is due to an implicit weighting towards smaller cities with fewer industries and frequently lower ratios. In general, city-technology pairs with more patents tend to have a greater relative fraction of breakthrough inventions.

2.2 The Ethnic Composition of US Invention

We model the labor mobility of a technology's workforce through the extent to which the technology relies on immigrant inventors. While immigration status is not contained in the patent database, one can determine the probable ethnicities of inventors through inventor names. USPTO patents must list at least one inventor, and multiple inventors are often listed. Our 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 similar. Several commercial ethnic name databases are utilized, and the name-matching algorithms have been extensively customized for the USPTO data. Kerr (2007) provides further details on the matching process, lists frequent ethnic names, and provides multiple descriptive statistics and quality assurance exercises.

The match rate is 99% for domestic inventors, and the process affords the distinction of nine ethnicities: Anglo-Saxon, Chinese, European, Hispanic, Indian, Japanese, Korean, Russian, and Vietnamese. Because the matching is done at the micro-level, greater detail on the ethnic composition of inventors is available annually on multiple dimensions like technologies, cities, and companies. 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.

Figure 1 illustrates the evolving ethnic composition of US inventors from 1975-2004. We group patents by the years in which they applied to the USPTO. For visual ease, Figure 1 does not include the Anglo-Saxon and European ethnic shares. They jointly decline from 90% of US domestic patents in 1975 to 76% in 2004. This declining share is partly due to the exceptional growth over the 30 years of the Chinese and Indian ethnicities, which increase from under 2% to 9% and 6%, respectively.

Figure 2 shows the share of patenting being undertaken by inventors not of Anglo-Saxon or European heritage for six broad technologies. For shorthand, we refer to this group of non-Anglo-Saxon or European origin inventors as immigrant inventors throughout this study, although this terminology is clearly a simplification. Some inventors with Anglo-Saxon or European surnames are immigrants to the US, just as some inventors with Vietnamese or Japanese surnames are in fact native citizens. Nevertheless, immigrants are a much larger share of the latter group, and this series principally follows the activity and contributions of Chinese and Indian ethnic inventors. Figure 2 highlights that immigrant inventors are more concentrated in high-tech industries like computers and pharmaceuticals.

The appendix provides greater detail on the spatial distribution of immigrant inventors. Immigrant SEs are relatively more present in gateway cities closer to their home countries (e.g., Chinese in San Francisco, Hispanics in Miami), and they are more spatially concentrated than general innovation and the population overall. The 1995-2004 immigrant inventor shares of San Francisco, New York, and Los Angeles are 22%, 10%, and 9%, respectively. This compares to 12%, 7%, and 6% shares for patenting more generally. Kerr (2009) documents how immigrant inventors are becoming more spatially concentrated over time, thereby increasing the agglomeration of US invention as whole.[8]

2.3 A Tale of 19 Cities

Tables 1 and 2 provide a preliminary analysis about the relationships among breakthrough inventions, immigrant inventors, and city patenting growth. Table 1 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

[8] Agrawal et al. (2008a,b) and Mandorff (2007) 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.

Pittsburgh, PA. The first set of three columns provides these two rankings and the rank changes evident.

The fourth column documents the average ratio of breakthrough to total patent shares for a city across the 36 technologies. The highest average city ratios are Minneapolis-St. Paul, MN, (1.96) and San Francisco, CA, (1.85); these cities both increased their rank by four spots. On the other hand, the lowest average city ratios are Pittsburgh, PA, (0.45) and Chicago, IL, (0.63). Both of these cities declined in rank. The bottom three rows of Table 1 show that this pattern generally holds. The average ratios for cities improving and declining rank are 1.33 and 0.85, respectively. A greater prevalence of breakthrough inventions in 1975-1984 clearly correlates with improved relative patenting outcomes by 1995-2004 among prominent cities.

The next set of three columns documents the share of each city's invention that is undertaken by Anglo-Saxon and European ethnicity inventors during the two periods. The secular decline in relative Anglo-Saxon and European invention is clearly evident in this sample. All 19 cities exhibit a lower share of Anglo-Saxon and European invention in 1995-2004 than earlier, with an average decrease of -12%. This is not a mechanical outcome but instead evidence of the pervasive growth in immigrant invention, which is documented in the last three columns. These shares are relative to the specific city, so they sum to 100%, and changes likewise sum to 0%.

We can take some suggestive evidence for the role of immigrant 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 immigrant inventors (+15%) than cities that lose rank (+9%). This difference is not due to convergence or mean reversion. The cities that lose rank start with a higher immigrant inventor share, but the cities that improve rank end the sample period with the larger share. By looking at inventor workforce compositions, these tabulations are also not keying in on changes in city patenting rates, city populations, or similar. The fractions suggest that cities that increased their patenting share underwent simultaneous shifts towards greater patenting by immigrant inventors. The overall correlation between rank change and immigrant invention growth is 0.54.

Table 2 demonstrates that these patterns hold when looking at changes across all cities. We split the sample using application years of patents (1975-1989, 1990-2004) and calculate the growth rate in patenting between the two periods by city. We divide cities by above and below median growth and also by quintiles of growth. Faster growth is consistently associated with a greater prevalence of breakthrough technologies and a more dramatic shift in the ethnic composition of a city's SE workforce towards immigrant inventors. In both cases, the difference between slow-growth and fast-growth cities is about two-fold.

3 Cross-Sectional Technology Growth Regressions

This section provides cross-sectional growth regressions to quantify localized patenting growth after breakthrough inventions. While it is tempting to employ the full cross-section of cities and technologies as the regression sample, this choice can lead to misleading results due to the non-random locations of invention and breakthrough inventions. We therefore select narrower control groups for most analyses to match better the pre-existing conditions when the breakthrough invention occurred. Conditional on this match, we believe the occurrence of breakthrough inventions can be treated as random or exogenous for studying subsequent patent migration. We also use differences across technologies in inventor mobility rates as a second identification strategy.

3.1 Graphical Analysis

Figure 3 illustrates our empirical design and these assumptions. For each of the 36 technologies, we identify the top ten cities in terms of levels of patenting in 1975-1984 (i.e., the total number of patents). There are two ties in the data, so this results in 362 city-technology pairs that account for about 60% of all US patenting. Within each technology, we then group these ten cities into the top five cities and the next five cities in terms of breakthrough patent ratios. As a final step, we sum the share of US patenting across these top five cites in all technologies for every year from 1975 onwards; we do the same for the next five cities per technology. By holding the city-technology assignments constant, this presents a simple lens for studying the migration of invention following breakthrough inventions.

Figure 3 shows that the shares of US patenting in these two groups are approximately equal at 30% of all US patenting for the pre-period of 1975-1984. Moreover, their growth patterns are similar. Conditional on being in the top ten cities for a technology, the relative fraction of breakthrough inventions is not systematically correlated with these pre-period traits. As one example, New York City is among the top five cities in 20 technologies and the next five cites in the other 16. Over the next 20 years, however, these pairs diverge. City-technologies with a higher prevalence of breakthrough innovations increase their share of US patenting to about 35%, while the comparable group declines by about half. This latter behavior is indicative of mean reversion from high past employment levels for city-industries without additional innovation (e.g., Simon 2004). While differences in patenting growth are not as stark as a tipping model would suggest, they do confirm that breakthrough inventions are sources of localized growth in patenting.

As a second feature, we separately calculate the shares of Anglo-Saxon/European and immigrant ethnic inventor patenting in these pairs. These groups are again quite comparable during the period before 1984. Immigrant shares tend to be slightly higher than Anglo-Saxon and European shares due to our focus on the largest patenting centers. The picture is again quite different after 1985. Immigrant inventors are very important for the growth of new breakthrough clusters, while they disproportionately leave the next five cities.

Figure 4 repeats this analysis with a different sample design. We select the top ten cities for each technology in terms of the breakthrough patent ratio. We do not sample on the overall level of city-technology patenting except to require that the city-technology have at least ten patents during the pre-period. We also require that at least one breakthrough patent exist in the city-technology, which we did not do when looking at the largest patenting centers in Figure 3, for a total of 341 observations. This approach thus includes a number of smaller city-technology pairs, and our analysis compares across these clusters with breakthrough patents in their levels of intensity.

By technology, we again divide these ten cities into the five cases with the highest breakthrough ratios and the next five cities. The top five cities have a smaller initial share of US patenting than the comparison group of the next five cities (3% versus 9%), and both shares are substantially smaller than in Figure 3. This is because, holding fixed the number of breakthrough inventions, the ratio (1) is larger for places with smaller shares of overall patenting. Thus, by selecting the top five ratios, we tend to select smaller places that experienced a disproportionately high number of breakthrough inventions. The control group grows from 9% of US patents during 1975-1984 and to around 14%. We would expect growth among this second group of cities since they possess the sixth through tenth highest concentrations of breakthrough patents. Growth for the treatment group is nevertheless stronger. The top five cities grow four-fold from 3% of US patents to 12%. Immigrant inventors are again very important in this growth.

Overall, these figures suggest that breakthrough inventions lead to localized patenting growth in controlled settings. This growth is not instantaneous, however, and it does not display strong tipping properties. Second, immigrant inventors appear important in this process. There are limits, however, to the conclusions that can be drawn from these graphs. They do not control for technology-level differences in patenting growth rates (e.g., the surge of software patents), differences in regional growth, and similar issues. By summing across city-technology pairs, we are also weighting larger patenting groups more heavily.

3.2 Growth Regressions

To control for these additional features, we employ cross-sectional growth regressions at the city-technology level in Tables 3 and 4. We regress the log growth rate of patenting for a city-technology from 1975-1989 to 1990-2004 on the ratio of breakthrough inventions to total inventions during the 1975-1984 period. We thus no longer sum the data into the top five and next five cities, but instead treat each observation individually. Table 3 corresponds to the sample design of the top ten innovation centers; Table 4 considers the ten highest breakthrough ratios for each technology regardless of city size. As the breakthrough ratio does not have an intuitive scale, we transform it to have zero mean and unit standard deviation.

In all regressions, we control for technology fixed effects and region fixed effects (nine Census regions). We also include measures of log city population in the pre-period, log growth in city population, and log city-technology patenting during the pre-period. This latter measure in particular captures the mean reversion properties of city patenting. The estimations are unweighted and report robust standard errors.

Column 1 of Table 3 finds that a one standard deviation increase in the ratio of breakthrough patents for the city-technology results in an 18% higher patent growth after 1990. This effect is statistically significant and economically important in magnitude. It is weaker than that implied in Figure 3, reflecting the tighter controls and the unweighted estimation strategy.

Column 2 interacts the breakthrough ratio with the extent to which the technology relies on immigrant inventors in the pre-period. This dependency averages 11% and ranges from 7% for "Receptacles" (sub-category 68) to 27% for "Semiconductor Devices" (sub-category 46). We again transform this variable to have zero mean and unit standard deviation before interacting; this restores the main effect for the ratio to its base value. The migration of invention around breakthrough patents is stronger among immigrant-intensive technologies, which we take to model the inherent labor mobility of the technology's SE workforce. For a technology that is one standard deviation above the mean in its immigrant inventor share (about 15%), the growth effect of breakthrough inventions is about 30%.

Columns 3-7 contain a variety of robustness checks. Columns 3 and 4 exclude computers and software (category 2) or electrical and electronics (category 4) patents; the latter includes semiconductors. These two technology groups have the most extreme patent growth, and Figure 2 emphasizes the exceptional growth in immigrant contributions within them. Similar results are found after these exclusions. Columns 5 and 6 show the patterns are robust to including region by technology fixed effects or city fixed effects in these regressions. These are very strict frameworks that compare variation in technology breakthroughs within local areas. They confirm that our results are not due to unmodeled factors operating at the city or regional levels. Finally, Column 7 finds similar results when expanding the sample to include all potential cities for each technology.[9]

[9] As a precaution, we cap patent growth rates at a ten-fold increase or decline, which affects about 2% of the

Table 4 repeats this analysis with the sample modified to be the ten largest breakthrough ratios for each technology as in Figure 4. Included city-technologies must have at least one breakthrough patent and ten total patents during the 1975-1984 pre-period. The pattern of findings is quite similar to Table 3. The growth effects tend to be marginally weaker in both economic magnitude and statistical significance. This is to be expected given the focus on just variation within the top ten breakthrough areas.

We have performed a variety of extensions on this analysis. First, we find very similar results when using narrower technology definitions. The 36 sub-categories of the USPTO system are an aggregation of over 400 patent classes. Examples of patent classes include "Refrigeration", "Chemistry: Electrical and Wave Energy", "Electrical Resistors", and "Cryptography". We developed a sample that includes all patent classes with at least ten cities having ten patents or more during 1975-1984. The elasticities at this level are very similar to those using sub-categories. We prefer the latter aggregation given their more stable definition and better measurement.[10]

Second, varying the threshold for assigning breakthrough inventions does not substantively change our results. We examined a range from the 90th percentile of citations to the 99.9th percentile. For the sample of the ten largest cities for each technology, the main effect is mostly constant across thresholds. The only change is that the interaction effect with the immigrant intensity in the industry increases with higher thresholds. Likewise, similar patterns are found when exploiting variation among the ten highest relative concentrations of breakthrough patents, although the sample size is too small for meaningful variation with the 99.9th percentile framework.

Finally, there is a potential endogeneity problem in the identification of breakthrough patents. Unmodeled factors may contribute to both higher breakthrough shares and also higher overall numbers or levels of patents, causing our regressions to be upward biased. This bias could be accentuated in this context due to our identification of breakthrough patents with subsequent citations. If citations are more frequent within cities than across them (e.g., Jaffe et al. 1993; Thompson 2007), we could in part be identifying breakthrough patents because of abnormal patenting growth in the area. To confirm this effect is not driving our findings, we tested

final sample. We find almost exactly the same outcomes without this trimming (e.g., a 0.183 (0.038) coefficient versus 0.181 (0.037) in Column 1 of Table 3), but we do not want to overly emphasize extreme growth cases. We also find very similar results when using growth formulations from Davis et al. (1996) and Autor et al. (2007). These formulations compare growth to the average value of patenting in the two periods, which naturally limits the scope for outliers. We have finally confirmed that our results do not depend upon on any one city or technology.

[10] Patent classes also afford a more sophisticated treatment of software patents, which can spill out of the computers category and are often difficult to identify. Hall and MacGarvie (2008) identify classes influenced by software patents by examining the patenting of major software firms. Megan MacGarvie kindly provided for this study a list of these classes. The patent class results are robust to dropping these classes. See Graham and Mowery (2004), Hall (2005), and Hall and MacGarvie (2008) for further details on software patents.

identifying top citation patents using only citations outside of the local area. This formulation delivers very similar results.

4 Immigrants and Spatial Adjustments in Innovation

The cross-sectional regressions in Section 3 suggest that migration is faster in technologies that rely more heavily on immigrant SEs. This interaction is of direct interest given the US' disproportionate reliance of immigrant inventors, and it further provides a window into how labor mobility governs industry migration rates. This section further characterizes these relationships. We first review why immigrants are more spatially mobile than their native SE counterparts. We then discuss how the Immigration Act of 1990 brought about an exogenous inflow in SE immigration. We use this natural experiment to confirm the causal role of immigrants in spatial technology adjustments within the US. Indirectly, this exercise also confirms shifts in localized patenting following breakthrough innovations by studying where these immigrants located.[11]

4.1 The Spatial Mobility of Immigrant SEs

The heightened spatial mobility of immigrants for SE descends from two sources. First, immigrants generally have greater rates of internal mobility once residing in the US. The appendix presents descriptive tabulations from the 1980-2000 Census of Populations which we summarize here. Among bachelor's-educated SEs over the age of 35, 16% of immigrants report moving states in the past five years compared to 12% of natives. The internal mobility rate is even more striking at 22% for Chinese and Indian SEs. All of these SE migration rates are substantially higher than the 7% rate in the general population, reflecting the greater mobility of technical workers in many countries (e.g., Dahl and Sorenson, this issue).[12]

Second, and more importantly, the initial location decisions of immigrant SEs are perhaps the easiest margin through which to adjust spatial invention patterns. The rapid expansion of patenting following a breakthrough innovation often leads firms in that area to recruit foreign workers. 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. Firms have the capacity to direct where immigrant workers are to

[11] An earlier version of this paper used this reform to demonstrate that increases in immigrant inventor populations for a technology resulted in faster general migration of patenting across cities, without reference to which group of cities were growing or declining in terms of patent shares. This analysis employed reallocation metrics similar to Davis et al. (1996) and Autor et al. (2007). These results are available upon request.

[12] The greater general mobility of technical workers actually weakens the comparative advantage of immigrants for spatial adjustments in SE compared to general work (e.g., Borjas 2001). Nonetheless, immigrants account for a greater fraction of migration among SE workers than in the general population in the US due to their larger representation.

locate under many temporary visa categories, most notably the H-1B category that is very influential for SE and computer-related occupations. Moreover, the legal attachment of many temporary immigrants to their sponsoring firms make it easier for firms to retain inventors in their selected cities. Many of these arguments would further apply to foreign students graduating from US universities. These students are a primary source for expansions of the US SE workforce and often rely on employer-sponsored visas for remaining in the US.

Even though new immigration represents a small part of the overall SE workforce in terms of levels, it accounts for a substantial share of the net moves in SE placements. Immigrants over the past five years represent 6% of the SE workforce in the 2000 Census but 25% of the net moves. This contribution is somewhat greater than the 17% of net moves due to internal migration by existing immigrants. Combining these effects, immigrants account for about 42% of effective moves in the 2000 Census, despite only being 24% of the bachelor's educated SE workforce (and 12% of the overall workforce). These forces help explain the mechanisms underlying faster spatial shifts among immigrant-dependent technologies.

4.2 The Immigration Act of 1990

The US immigration system significantly restricted the inflow of immigrant SEs from certain nations prior to its reform with the Immigration Act of 1990 (1990 Act). We use the changes in the quotas surrounding the 1990 Act to model an exogenous surge in immigrant SEs. US immigration law applies two distinct quotas to numerically restricted immigrants.[13] Both of these quotas were increased by the 1990 Act, and their combined change dramatically released pent-up immigration demand from SEs 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.[14] Larger nations are more constrained by uniform 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

[13] 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 about 60% of all immigrants, most immigrant SEs obtain permanent residency through numerically restricted categories (75%). Immigrant SE inflows through the unrestricted categories are stable in the years surrounding the 1990 reform, so we concentrate on the numerically restricted grouping.

[14] 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.

to 196,000.[15] Moreover, the relative admissions of high-skill professionals to low-skill workers significantly increased within the employment-based admissions.

The uniform country quotas and weak employment preferences constrained high-skill immigration from large nations, and Table 5 documents long waiting lists for Chinese, Indian, and Filipino applicants around the reform. When the 1990 Act simultaneously raised both of these quotas, the number of immigrant SEs entering the US dramatically increased. Figure 5 uses records from the Immigration and Naturalization Service (INS) to detail the response. It plots the number of immigrant SEs 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 SE 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 SEs. Immigration further surged in 1992-1995 as the pent-up demand was released. On the other hand, low-skill immigration from China and India did not respond to the 1990 Act.[16]

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. Expected stay rates increased 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.

To be clear, the legal change in quotas was not specific to either SE immigration or to certain countries like China and India. The quota change technically applied to all countries and employment-based admissions. The reduced-form approach exploits the fact that these general changes produced a large SE inflow from several countries constrained under the previous system. We formally define the reduced-form estimator after discussing the data structure for the panel estimations.

[15] The employment limit increased to 140,000, but 120,120 corresponds to the previously restricted categories.
[16] Kerr (2008) documents these calculations from immigrant-level INS records.

4.3 Data Structure for Interaction Estimations

To allow for a panel analysis of these reforms, we organize the data around the top ten cities for each technology in terms of breakthrough patent ratios that we developed earlier. We sum the patent data into four blocks of five years by technology for the top five cities and the comparison group of the next five cities. These five-year blocks start with 1985-1989 and end with 2000-2004. We calculate the log growth rate in patenting for each time period from the previous period. We use data from 1975-1984 to calculate the first period's growth rate and initial immigrant shares by technology, but we exclude the period in which the breakthrough technologies occurred from the regressions. In total, we have 288 observations representing 36 technologies, four time periods, and two groups of cities.

The linear interaction specification takes the form,

$$\Delta \ln(\mathrm{PAT}_{c,j,t}) = \phi_{c,j} + \eta_t + \beta \cdot [\mathrm{ISE}_{j,t_0} \cdot \Delta \ln(\mathrm{ISE}_t)] + \gamma \cdot [\mathrm{TOP5}_c \cdot \mathrm{ISE}_{j,t_0} \cdot \Delta \ln(\mathrm{ISE}_t)] + \epsilon_{c,j,t}, \quad (2)$$

where c indexes city groups, j indexes technologies, and t indexes time periods. $\phi_{c,j}$ is a vector of cross-sectional fixed effects that removes systematic patterns in growth rates by each city group and technology pair. η_t is a vector of time period fixed effects. These fixed effects create a very stringent empirical environment that focuses on discontinuities created by the 1990 Act and how they affected immigrant-intensive technologies.

Turning to the regressors of interest, ISE_{j,t_0} is the share of immigrant patenting by technology in the pre-period of 1975-1984. This variable is identical to the one employed in the cross-sectional estimations. We again normalize the dependency to have zero mean and unit standard deviation. $\Delta \ln(\mathrm{ISE}_t)$ is the log growth in immigrant SE workers from the previous period. We model this term both through actual immigration trends and also through the reduced-form estimator constructed below. In both approaches, this variable is national in scope, not specific to a city group or to a technology. Finally, $\mathrm{TOP5}_c$ is an indicator variable for the top five city group. The main effects of the interacted variables are controlled for by the fixed effects.

The β coefficient measures the differential impact of higher national immigration inflows on patenting growth in immigrant-intensive technologies relative to other technologies in the sixth through tenth ranked breakthrough cities. We do not have a strong prior about the size of the β coefficient given the narrowly selected sample and strict controls. The γ coefficient measures the additional patenting growth in the five most important breakthrough centers relative to their peers. Finally, $\beta + \gamma$ measures the full impact for the top five cities. A positive and statistically significant γ coefficient provides strong evidence of immigrants aiding the growth of new clusters surrounding breakthrough innovations.

4.4 Interaction Estimations

Table 6 estimates specification (2) using the national growth in immigrant patenting to model $\Delta \ln(\text{ISE}_t)$. The base effect β is not very strong or precisely measured. Increases in national immigrant patenting are, however, associated with strong growth among the top five breakthrough cities for each technology ($\beta + \gamma$). The differences between these two groups, the γ coefficient, is economically important in size and statistically significant at the 10% level. Comparable results are found when excluding very immigrant-intensive sectors in Columns 2 and 3. Likewise, Column 4 finds similar patterns when including broad technology by year fixed effects using the divisions illustrated in Figure 2.

Table 7 substitutes the reduced-form quota changes. 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 5 makes this assumption more reasonable for the purposes of modelling the discontinuity of the 1990 Act. We then define QUOTA_t as the effective quota for immigrant SEs 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,

$$\text{ISE-RF}_t = \sum_{s=1}^{5} \left(\text{QUOTA}_{t-s} + \text{QUOTA}_{t-s-1} + \text{QUOTA}_{t-s-2} \right), \tag{3}$$

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 immigrant SEs increases. While the quotas are applied at the country level, the same effective quota shift is present for all immigrant SEs subject to a multiplicative constant. This scaling is not important for our panel estimation techniques utilizing log variables, so we keep the simpler formula.

The results in Table 7 are very similar to Table 6. The overall pattern suggests that larger immigration inflows are associated with faster patenting growth for immigrant-intensive sectors in places where breakthrough inventions have occurred. These effects are particularly acute among the top five centers of past breakthroughs.

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 that 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. Table 8 documents these results in a panel setting where we model just the patenting growth in the top five cities. Both placebo estimators are statistically insignificant and have point estimates less than half the economic magnitude of the true reform. This stability is comforting for the reduced-form design.

The appendix reports a second robustness check. To be consistent with the earlier sections, we did not build into the reduced-form estimator (3) that the vast majority of the SE immigration inflow was Chinese and Indian SEs. These two ethnicities account for the majority of inventors not of Anglo-Saxon and European heritage, so the difference in modelling assumptions is relatively small. Nonetheless, the appendix documents tests that separate Chinese and Indian interactions from other immigrant ethnicities. The patent growth effects following the 1990 Act are particularly strong in technologies that rely heavily on Chinese and Indian inventors. This localized impact, even among immigrant inventor groups, provides an additional measure of confidence in the empirical design.

5 Conclusions

This study has employed several approaches to assess whether centers of breakthrough innovations experience subsequent growth in innovation relative to their peer locations. The evidence strongly supports this conclusion. The underlying mobility of the workforce also appears quite important for the speed at which spatial adjustments occur. We noted that immigrants, and particularly new immigration to the US, can facilitate faster spatial reallocation. Patenting migrates to locations with breakthrough technologies faster for technologies that employ immigrant inventors intensively than other technologies. These findings provide qualitative support for theoretical models like Duranton (2007).

There are several important areas for future research. One important step requires linking shifts in technology location to shifts in industry production. Quantifying the time required for both building innovation centers and building production centers will help evaluate the dynamics of industry churning and model speeds of urban evolutions. Second, future research should quantify other determinants of the speed at which these transitions occur. Examples include the size of technology advances, the industrial organization of the industry, and the dependency upon natural resources. Finally, this study and the underlying theory models take breakthrough inventions outside of the existing industry core to be exogenous or random. It would appear important to evaluate whether this is truly so.

References

[1] Agrawal, A., Kapur, D., McHale, J., 2008a. How do spatial and social proximity influence knowledge flows? Evidence from patent data, Journal of Urban Economics 64, 258-269.

[2] Agrawal, A., Kapur, D., McHale, J., 2008b. Brain drain or brain bank? The impact of skilled emigration on poor-country innovation, NBER Working Paper 14592.

[3] Agrawal, A., Cockburn, I., Rosell, C., 2010. Not invented here? Innovation in company towns, Journal of Urban Economics, this issue.

[4] Arzaghi, M., Davis, J., 2005. Spatial mobility and geographic concentration, Working Paper.

[5] Arzaghi, M., Henderson, J.V., 2008. Networking off madison avenue, Review of Economic Studies 75:4, 1011-1038.

[6] Autor, D., Kerr, W., Kugler, A., 2007. Does employment protection reduce productivity? Evidence from U.S. states, Economic Journal 117:521, 189-217.

[7] Bartel, A., 1989. Where do the new immigrants live?, Journal of Labor Economics 7:4, 371-391.

[8] Beardsell, M., Henderson, J.V., 1999. Spatial evolution of the computer industry in the USA, European Economic Review 43:2, 431-456.

[9] Black, D., Henderson, J.V., 1999. Urban evolution of population and industry in the United States, American Economic Review 89:2, 321-327.

[10] Borjas, G., 1994. Economics of immigration, Journal of Economic Literature 32, 1667-1717.

[11] Borjas, G., 2001. Does immigration grease the wheels of the labor market?, Brookings Papers on Economic Activity 2001:1, 69-119.

[12] Borjas, G., 2003. The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market, The Quarterly Journal of Economics 118:4, 1335-1374.

[13] Borjas, G., 2004. Do foreign students crowd out native students from graduate programs?, NBER Working Paper 10349.

[14] Card, D., 2001. Immigrant inflows, native outflows, and the local labor market impacts of higher immigration, Journal of Labor Economics 19:1, 22-64.

[15] Carlino, G., Chatterjee, S., Hunt, R., 2007. Urban density and the rate of invention, Journal of Urban Economics 61, 389-419.

[16] Carlino, G., Hunt, R., 2007. Innovation across U.S. industries: The effect of local economic characteristics, Working Paper.

[17] Chen, Y., Rosenthal, S., 2008. Local amenities and life-cycle migration: Do people move for jobs or fun?, Journal of Urban Economics 64, 519-537.

[18] Dahl, M., Sorenson, O., 2010. The migration of technical workers, Journal of Urban Economics, this issue.

[19] Davis, S., Haltiwanger, J., Schuh, S., 1996. Job Creation and Destruction, MIT Press, Cambridge, MA.

[20] Delgado, M., Porter, M., Stern, S., 2008. Convergence, clusters and economic performance, Working Paper.

[21] Delgado, M., Porter, M., Stern, S., 2009. Entrepreneurship in clusters, Working Paper.

[22] Dumais, G., Ellison, G., Glaeser, E., 2002. Geographic concentration as a dynamic process, Review of Economics and Statistics 84, 193-204.

[23] Duranton, G., 2007. Urban evolutions: The fast, the slow, and the still, The American Economic Review 97:1, 197-221.

[24] Ellison, G., Glaeser, E., Kerr, W., 2009. What causes industry agglomeration? Evidence from coagglomeration patterns, The American Economic Review, forthcoming.

[25] Findeisen, S., Südekum, J., 2008. Industry churning and the evolution of cities: Evidence for Germany, Journal of Urban Economics 64, 326-339.

[26] Friedberg, R., Hunt, J., 1995. The impact of immigrants on host country wages, employment and growth, Journal of Economic Perspectives 9:2, 23-44.

[27] Gabriel, S., Rosenthal, S., 2004. Quality of the business environment versus quality of life: Do firms and households like the same cities?, Review of Economics and Statistics 86, 438-444.

[28] Glaeser, E., Kallal, H., Scheinkman, J., Shleifer, A., 1992. Growth in cities, Journal of Political Economy 100, 1126-1152.

[29] Glaeser, E., Kerr, W., 2009. Local industrial conditions and entrepreneurship: How much of the spatial distribution can we explain?, Journal of Economics and Management Strategy 18:3, 623-663.

[30] Glaeser, E., Kerr, W., Ponzetto, G., 2010. Clusters of entrepreneurship, Journal of Urban Economics, this issue.

[31] Graham, S., Mowery, D., 2004. Software patents: Good news or bad news?, Working Paper.

[32] Greenwood, M., 1997. Internal migration in developed countries, in Rosenzweig, M., Stark, O. (Eds.), Handbook of Population and Family Economics, Elsevier, Amsterdam.

[33] Griliches, Z., 1990. Patent statistics as economic indicators: A survey, Journal of Economic Literature 28:4, 1661-1707.

[34] Hall, B., 2005. Exploring the patent explosion, Journal of Technology Transfer 30, 35-48.

[35] Hall, B., Jaffe, A., Trajtenberg, M., 2001. The NBER patent citation data file: Lessons, insights and methodological tools, NBER Working Paper 8498.

[36] Hall, B., MacGarvie, M., 2008. The private value of software patents, NBER Working Paper 12195.

[37] Henderson, J.V., Kuncoro, A., Turner, M., 1995. Industrial development in cities, Journal of Political Economy 103:5, 1067-1090.

[38] Holmes, T., 1998. The effects of state policies on the location of manufacturing: Evidence from state borders, Journal of Political Economy 106, 667-705.

[39] Hunt, J., 2009. Which immigrants are most innovative and entrepreneurial? Distinctions by entry visa, NBER Working Paper 14920.

[40] Hunt, J., Gauthier-Loiselle, M., 2008. How much does immigration boost innovation?, NBER Working Paper 14312.

[41] Jacobs, J., 1970. The Economy of Cities, Vintage Books, New York, NY.

[42] Jaffe, A., Trajtenberg, M., Henderson, R., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations, The Quarterly Journal of Economics 108:3, 577-598.

[43] Kerr, S., Kerr, W., 2008. Economic impacts of immigration: A survey, HBS Working Paper 09-013.

[44] Kerr, W., 2007. The ethnic composition of US inventors, HBS Working Paper 08-006.

[45] Kerr, W., 2008. Ethnic scientific communities and international technology diffusion, Review of Economics and Statistics 90:3, 518-537.

[46] Kerr, W., 2009. The agglomeration of U.S. ethnic inventors, forthcoming in Glaeser, E. (Ed.), Economics of Agglomeration, University of Chicago Press, Chicago, IL.

[47] Kerr, W., Lincoln, W., 2008. The supply side of innovation: H-1B visa reforms and US ethnic invention, HBS Working Paper 09-005.

[48] Klepper, S., 2010. The origin and growth of industry clusters: The making of silicon valley and detroit, Journal of Urban Economics, this issue.

[49] Mandorff, M., 2007. Social networks, ethnicity, and occupation, Working Paper.

[50] Marshall, A., 1920. Principles of Economics, MacMillan and Co., London, UK.

[51] Matloff, N., 2003. On the need for reform of the H-1B non-immigrant work visa in computer-related occupations, University of Michigan Journal of Law Reform.

[52] Peri, G., 2007. Higher education, innovation and growth, in Brunello, G., Garibaldi, P., Wasmer, E. (Eds.), Education and Training in Europe, Oxford University Press, Oxford, UK.

[53] Rosenthal, S., Strange, W., 2003. Geography, industrial organization, and agglomeration, Review of Economics and Statistics 85:2, 377-393.

[54] Saxenian, A., 1994. Regional Advantage: Culture and Competition in Silicon Valley and Route 128, Harvard University Press, Cambridge, MA.

[55] Saxenian, A., 1999. Silicon Valley's New Immigrant Entrepreneurs, Public Policy Institute of California, San Francisco, CA.

[56] Simon, C., 2004. Industrial reallocation across US cities 1977–1997, Journal of Urban Economics 56, 119-143.

[57] Stephan, P., Levin, S., 2001. Exceptional contributions to US science by the foreign-born and foreign-educated, Population Research and Policy Review 20:1, 59-79.

[58] Thompson, P., 2006, Patent citations and the geography of knowledge spillovers: Evidence from inventor- and examiner-added citations, Review of Economics and Statistics 88:2, 383-388.

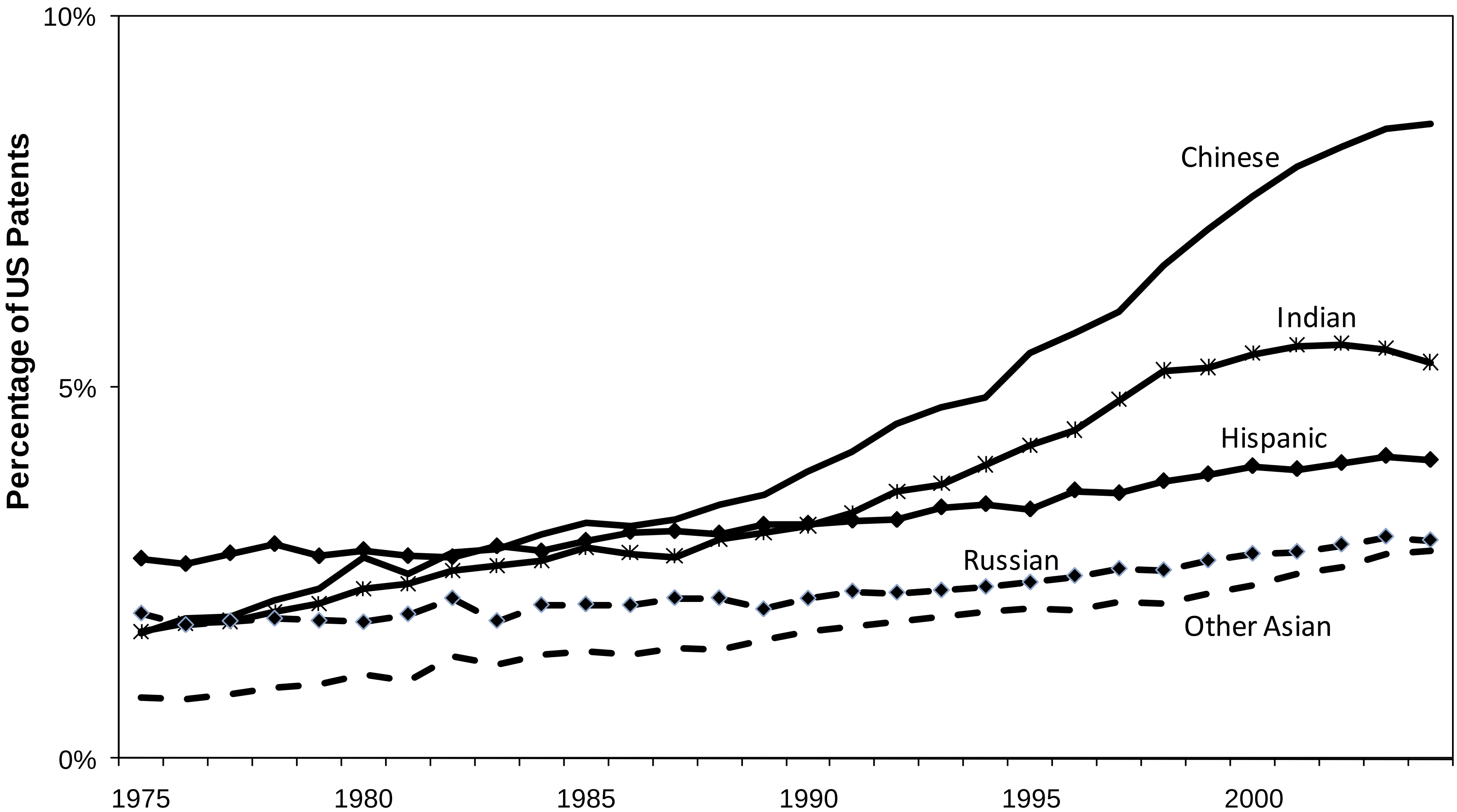
[59] Thompson, P., Fox-Kean, M., 2005. Patent citations and the geography of knowledge spillovers: A reassessment, American Economic Review 95:1, 450-460.

[60] Trajtenberg, M., 1990. A penny for your quotes: Patent citations and the value of innovations, The Rand Journal of Economics 21:1, 172-187.

[61] Wadhwa, V., Saxenian, A., Rissing, B., Gereffi, G., 2007. America's new immigrant entrepreneurs I, Working Paper.

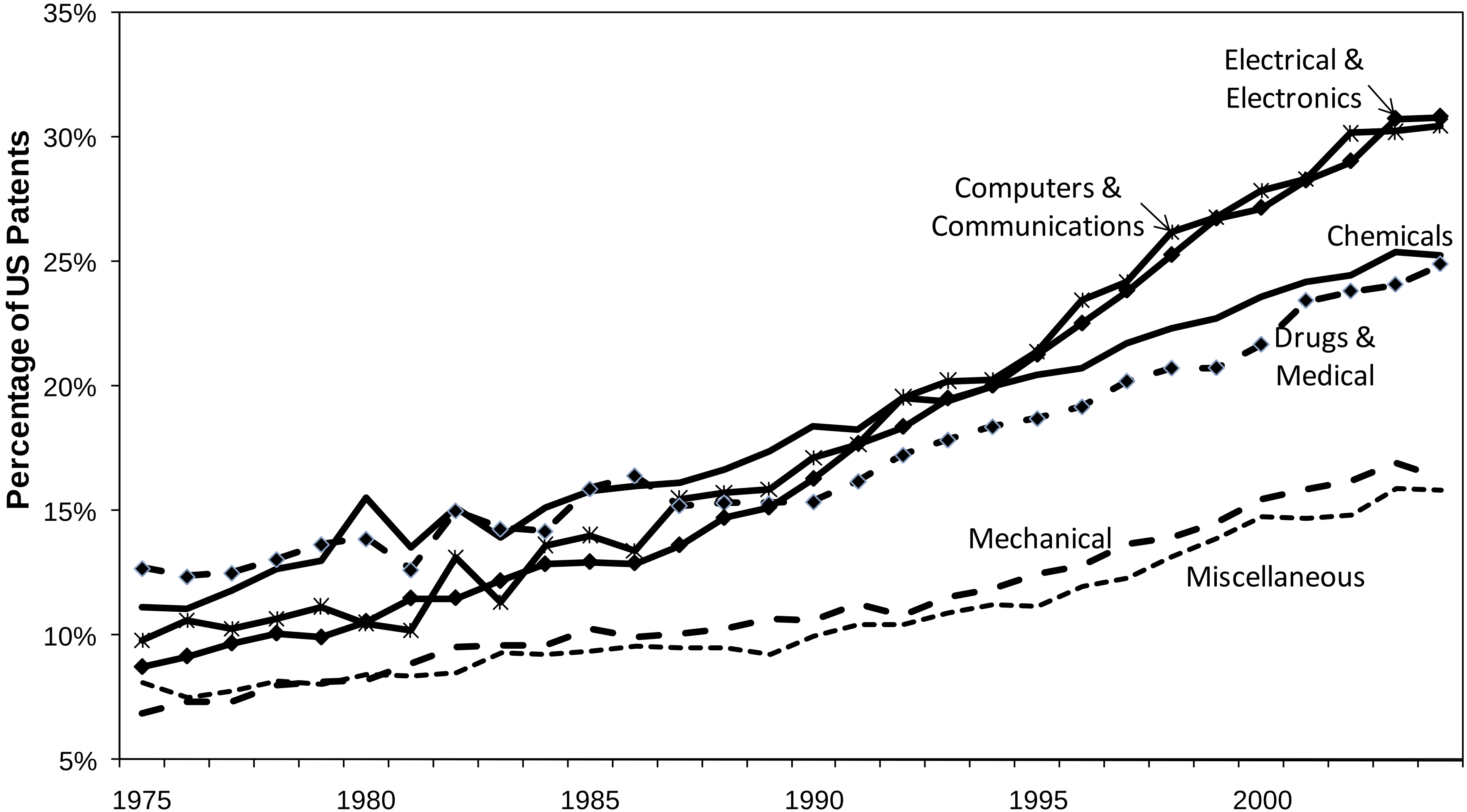
[62] Wallace, N., Walls, D., 2004. Agglomeration economies and the high-tech computer cluster, Working Paper.

Fig. 1: Growth in US Immigrant Ethnic Patenting



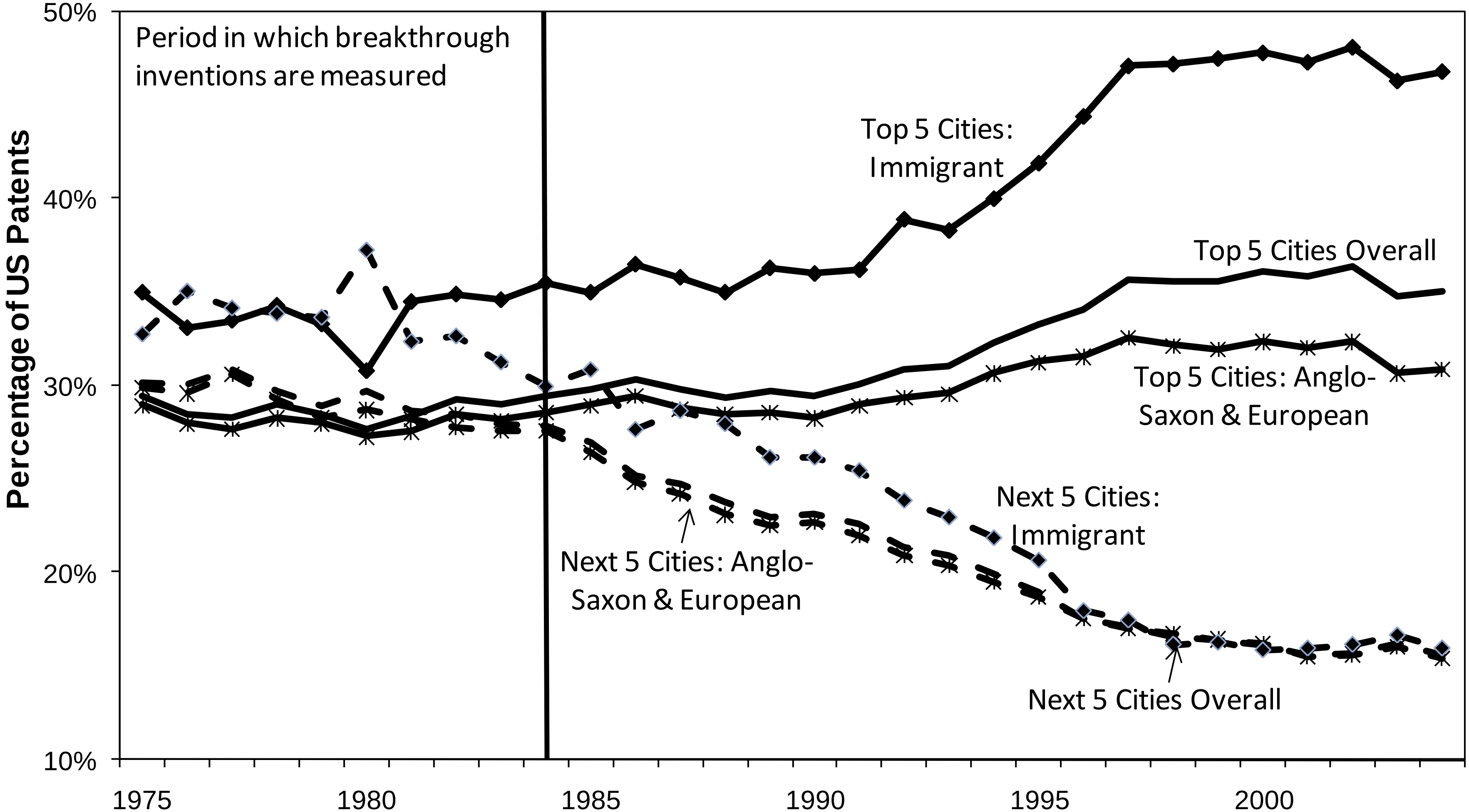
Notes: Trends describe the growing shares of US patents filed by inventors of immigrant ethnicities. Only patents with inventors residing in the US are included. Patents are grouped by application years. Inventor ethnicity is determine through inventor names listed on patents. Anglo-Saxon (75%→63%) and European (16%→13%) contributions are excluded for visual clarity. Other Asian contributions include Japanese, Korean, and Vietnamese contributions.

Fig. 2: Immigrant Ethnic Contributions by Technology



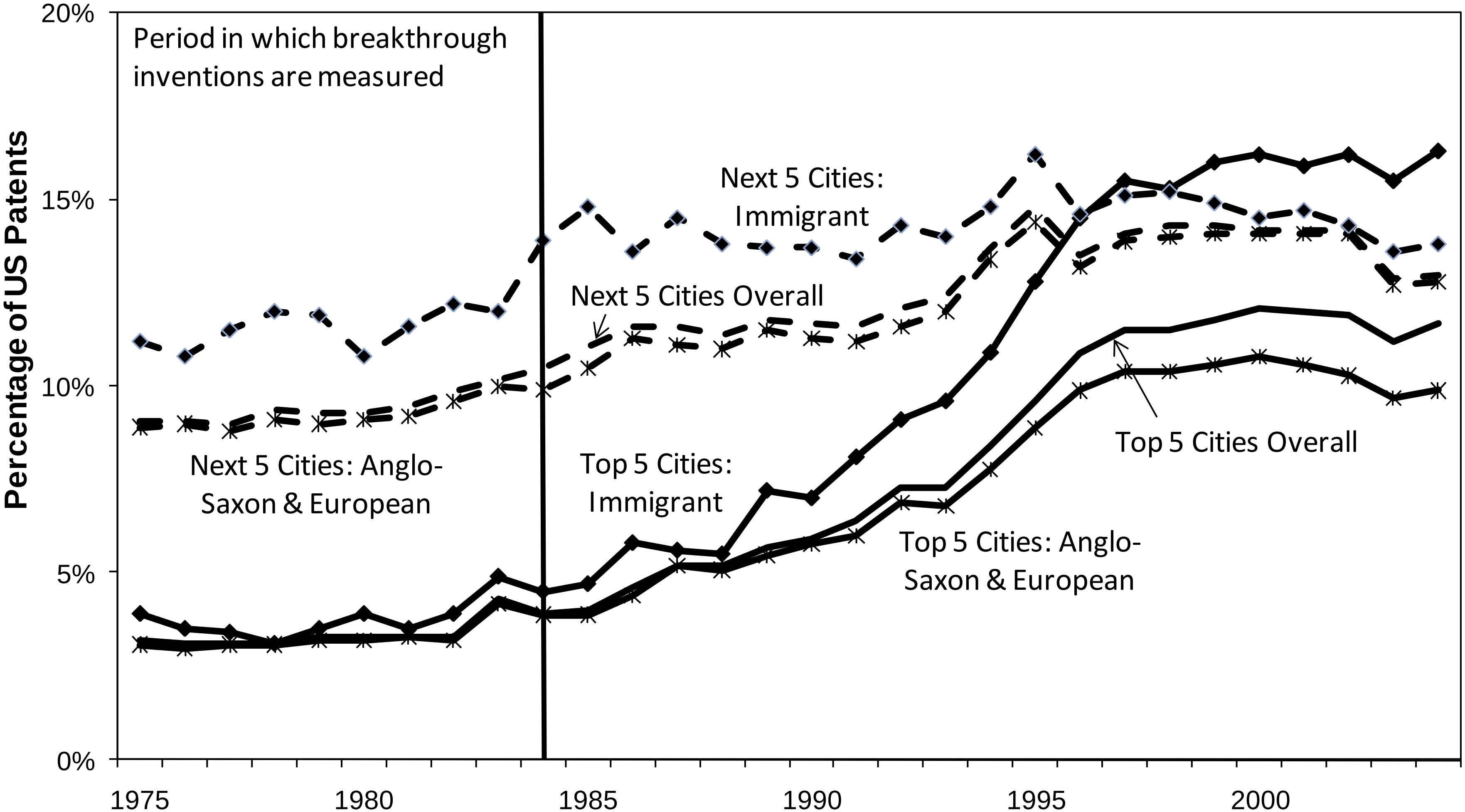
Notes: See Figure 1. This figure describes the share of US patenting by broad technology category undertaken by inventors not of Anglo-Saxon or European heritage. Growth in immigrant contributions is strongest in advanced technologies.

Fig. 3: Localized Patenting Growth after Breakthroughs
Ten Largest Cities per Technology



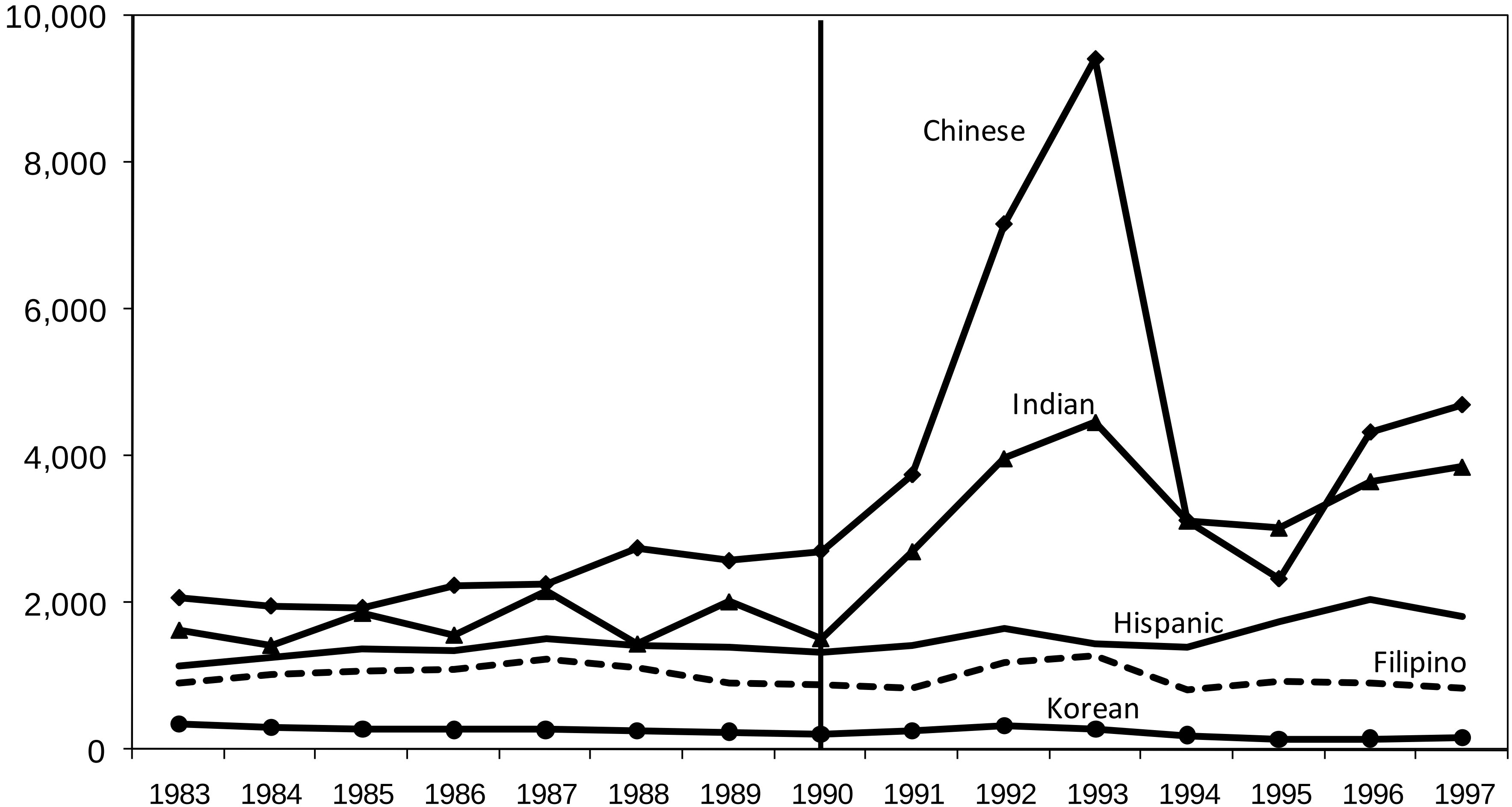
Notes: Figure presents localized growth in US patenting following breakthrough technologies. The sample includes the top cities per technology in 1975-1984 in terms of numbers of patents. Within each technology, these ten cities are grouped into the top five cities and the next five cities in terms of breakthrough patent ratios. These ratios are the city's share of breakthrough patents for the technology divided by the city's total share of patents for the technology. Breakthrough patents are defined as the top one percent of each technology's 1975-1984 patents in terms of citations subsequently received. Included city-technology pairs are held constant to measure the migration of innovation following breakthroughs. Shares for Anglo-Saxon/European ethnicity inventors and immigrant ethnicities are also provided for each series. Immigrant ethnicities play a disproportionate role in the migrations.

Fig. 4: Localized Patenting Growth after Breakthroughs
Ten Highest Concentrations of Breakthroughs



Notes: See Figure 3. The sample is adjusted in this graph to be the top ten centers per technology in terms of breakthrough patent ratios. We do not sample on the overall level of city-technology patenting except to require that the city-technology have at least ten patents and one breakthrough patent during the pre-period. Within each technology, the ten cities are again grouped into the top five cities and the next five cities by the breakthrough ratio. The top five cities have a smaller initial share of US patenting than the comparison group of the next five cities (3% versus 9%), and both shares are substantially smaller than in Figure 3. This is because, holding fixed the number of breakthrough inventions, the ratio is larger for smaller places. Even relative to this peer group, patent growth in the top five cities is stronger. Immigrant inventors are again very important in this growth.

Fig. 5: S&E Immigration After Immigration Act of 1990



Notes: Figure presents permanent residency admissions to the US for immigrants with science and engineering occupations. The vertical line marks the passage of the Immigration Act of 1990 that took effect in October 1991. Immigration for ethnicities is an aggregate of country-level immigration within each ethnicity.

Table 1: Descriptive Statistics for Prominent Patenting Cities

	City Rank			City's Average Ratio of Highly Cited Patents 1975-1984	Anglo-Saxon and European Ethnic Inventor Share of City			Immigrant Ethnic Inventor Share of City		
	1975-1984	1995-2004	Rank Change		1975-1984	1995-2004	Share Change	1975-1984	1995-2004	Share Change
San Francisco, CA	5	1	+4	1.85	84%	61%	-23%	16%	39%	23%
New York, NY	1	2	-1	0.91	85%	69%	-16%	15%	31%	16%
Los Angeles, CA	4	3	+1	1.05	87%	69%	-17%	14%	31%	17%
Boston, MA	6	4	+2	1.48	89%	78%	-11%	11%	22%	11%
Chicago, IL	2	5	-3	0.63	88%	80%	-8%	12%	20%	8%
Detroit, MI	7	6	+1	0.85	89%	81%	-8%	11%	19%	8%
Minneap.-St. Paul, MN	11	7	+4	1.96	92%	86%	-6%	8%	14%	6%
Philadelphia, PA	3	8	-5	0.76	87%	78%	-10%	13%	23%	10%
Dallas-Fort Worth, TX	13	9	+4	1.02	92%	74%	-18%	9%	26%	18%
Austin, TX	36	10	+26	0.87	90%	76%	-14%	10%	24%	14%
San Diego, CA	26	11	+15	1.32	89%	73%	-16%	12%	28%	16%
Seattle, WA	21	12	+9	1.59	92%	79%	-13%	8%	21%	13%
Rochester, NY	12	13	-1	1.15	87%	81%	-6%	13%	19%	6%
Houston, TX	9	14	-5	0.64	91%	79%	-12%	9%	21%	12%
Boise City, ID	161	15	+146	1.28	96%	74%	-22%	4%	26%	22%
Cleveland, OH	8	21	-13	0.68	89%	84%	-5%	11%	16%	5%
Cincinnati, OH	15	22	-7	1.14	93%	86%	-7%	7%	14%	7%
Albany-Sch.-Troy, NY	14	25	-11	1.28	86%	76%	-10%	14%	24%	10%
Pittsburgh, PA	10	26	-16	0.45	89%	83%	-5%	11%	17%	5%
Top Cities Overall				1.10	89%	77%	-12%	11%	23%	12%
- Those Improving Rank				1.33	90%	75%	-15%	10%	25%	15%
- Those Losing Rank				0.85	88%	79%	-9%	12%	21%	9%

Notes: Table documents city patenting rank, 1975-1984 breakthrough patent ratios, and ethnic compositions of inventors for prominent patenting cities. Listed cities include the top 15 patenting cities in 1975-1984 and 1995-2004, for a total of 19 cities. City's average ratio of highly cited patents is an average across technologies of the city's share of the top one percent of the technology's 1975-1984 patents in terms of subsequent citations divided by the city's share of all patents in the technology. A ratio of one indicates that breakthrough patents occurred in the city in equal proportion to its general patenting behavior. The ratio is only calculated for city-technologies with ten or more patents in 1975-1984. Ethnic inventor shares are relative to each city's inventor population in the indicated period. Immigrant Ethnic Inventor Share includes Chinese, Indian, Hispanic, Japanese, Korean, Russian, and Vietnamese contributions. The bottom three rows document that cities improving rank disproportionately had breakthrough patents and shifted their inventor compositions further towards immigrant ethnic inventors.

Table 2: Descriptive Statistics for All Cities

	City's Average Ratio of Highly Cited Patents 1975-1984	Anglo-Saxon and European Ethnic Inventor Share of City			Immigrant Ethnic Inventor Share of City		
		1975-1984	1995-2004	Share Change	1975-1984	1995-2004	Share Change
All 280 Cities	0.64	93%	87%	-6%	7%	13%	6%
- Below Median Growth	0.49	92%	88%	-4%	8%	12%	4%
- Above Median Growth	0.80	93%	85%	-8%	7%	15%	8%
- Q1 (Slowest Growth)	0.41	93%	90%	-3%	7%	10%	3%
- Q2	0.44	92%	88%	-4%	8%	12%	4%
- Q3	0.64	93%	85%	-8%	7%	15%	8%
- Q4	0.92	93%	87%	-6%	7%	13%	6%
- Q5 (Fastest Growth)	0.81	92%	85%	-7%	8%	15%	7%

Notes: Table extends Table 1 to consider variation across all 280 cities. Highly cited patent ratios are only calculated for city-technology pairs with at least 10 patents during 1975-1984. A total of 237 cities have at least one technology that meets this criterion.

Table 3: Localized Patenting Growth after Breakthrough Inventions - Ten Largest Cities per Technology

	Basic Regression	Adding Technology Interaction	Excluding Computers & Software	Excluding Electrical & Electronics	Including Reg. x Tech. Fixed Effects	Including City Fixed Effects	Examining All Cities per Tech.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is Log Growth in City-Technology Patenting, 1990-2004 v. 1975-1989 Regressions include Basic Controls, Region Fixed Effects, and Technology Fixed Effects						
City Breakthrough Patent Ratio for the Technology, 1975-1984	0.181 (0.037)	0.182 (0.033)	0.166 (0.033)	0.171 (0.033)	0.205 (0.063)	0.132 (0.033)	0.080 (0.014)
Interaction of City Breakthrough Ratio and Immigrant Inventor Share by Technology		0.112 (0.030)	0.106 (0.030)	0.125 (0.040)	0.138 (0.053)	0.099 (0.034)	0.061 (0.018)
Linear Combination of Effects for Unit Standard Deviation Increase in Technology's Immigrant Inventor Share		0.293 (0.039)	0.272 (0.039)	0.296 (0.048)	0.342 (0.067)	0.231 (0.048)	0.141 (0.022)
Adjusted R-Squared	0.61	0.61	0.57	0.63	0.63	0.72	0.38
Observations	362	362	322	290	362	362	2854

Notes: Regressions describe growth of patenting in cities where breakthrough inventions occurred during 1975-1984. The sample includes the top ten cities for each technology in terms of pre-period patenting levels. Technologies are classified through sub-categories of the USPTO classification system (36 in total); two ties result in a total sample size of 362 observations for the base regressions. The core regressor is the ratio of the city's share of breakthrough patents divided by the city's share of all patents for the technology. Breakthrough patents are identified as the top one percent of each technology's 1975-1984 patents in terms of citations subsequently received. Immigrant inventors shares are the percentages of 1975-1984 patents filed by inventors not of Anglo-Saxon and European heritage. These shares are calculated specific to each technology. Breakthrough patent ratios and immigrant inventors shares are both normalized to have zero mean and unit standard deviation before interacting. Regressions include log city population levels, log city population growth, log city-technology patenting for 1975-1989, region fixed effects, and technology fixed effects. Regressions are unweighted and report robust standard errors.

Table 4: Localized Patenting Growth after Breakthrough Inventions - Ten Largest Breakthrough Ratios

	Basic Regression	Adding Technology Interaction	Excluding Computers & Software	Excluding Electrical & Electronics	Including Reg. x Tech. Fixed Effects	Including City Fixed Effects	Examining Top 30 Cities per Tech.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is Log Growth in City-Technology Patenting, 1990-2004 v. 1975-1989 Regressions include Basic Controls, Region Fixed Effects, and Technology Fixed Effects						
City Breakthrough Patent Ratio for the Technology, 1975-1984	0.097 (0.054)	0.106 (0.052)	0.115 (0.058)	0.067 (0.056)	0.112 (0.081)	0.115 (0.050)	0.099 (0.019)
Interaction of City Breakthrough Ratio and Immigrant Inventor Share by Technology		0.109 (0.060)	0.110 (0.063)	0.124 (0.063)	0.193 (0.156)	0.090 (0.065)	0.079 (0.025)
Linear Combination of Effects for Unit Standard Deviation Increase in Technology's Immigrant Inventor Share		0.214 (0.055)	0.224 (0.068)	0.191 (0.057)	0.304 (0.167)	0.205 (0.074)	0.178 (0.029)
Adjusted R-Squared	0.42	0.43	0.41	0.49	0.41	0.61	0.39
Observations	341	341	307	273	341	341	1748

Notes: See Table 3. The sample is modified to consider variation among the ten largest breakthrough ratios for each technology. Included city-technologies must have at least one breakthrough patent and ten total patents during the 1975-1984 pre-period.

Table 5: Waiting Lists and Admissions Data 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 accompanying 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. Kerr (2008) provides further details on these tabulations.

Table 6: Interaction Estimations Employing US Immigrant Patenting Growth

	Base Interaction Estimation	Excluding Computers & Software	Excluding Electrical & Electronics	Including Category x Year FE
	(1)	(2)	(3)	(4)
	Dependent Variable is Log Patenting Growth Estimations include Panel Fixed Effects			
Δ Log Immigration Patenting x	0.079	0.056	0.215	-0.014
Initial Immigrant Dependency by Technology	(0.126)	(0.119)	(0.122)	(0.097)
Δ Log Immigration Patenting x	0.298	0.301	0.240	0.298
Initial Immigrant Dependency by Technology x	(0.169)	(0.157)	(0.198)	(0.117)
Top 5 Cities for Breakthrough Inventions				
Linear Combination of Effects for Full Effect	0.377	0.357	0.455	0.284
on Top 5 Cities	(0.113)	(0.102)	(0.158)	(0.092)
Adjusted R-Squared	0.39	0.37	0.40	0.48
Observations	288	256	232	288

Notes: Regressions describe growth of patenting in cities where breakthrough inventions occurred during 1975-1984. The patent data are summed into four blocks of five years by technology for the top five cities and the comparison group of the next five cities. These five-year blocks start with 1985-1989 and end with 2000-2004. The dependent variable is the log growth rate in patenting for each time period from the previous period. The 288 observations represent 36 technologies, four time periods, and two groups of cities. The core regressor is the national growth in immigrant patenting interacted with the technology's initial dependence on immigrant inventors. A second interaction characterizes the additional response in the top five cities relative to the next five cities. Main effects are absorbed into the panel fixed effects. Regressions are unweighted and cluster standard errors cross-sectionally.

Table 7: Interaction Estimations Employing Immigration Quotas Estimator

	Base Quotas Estimation	Excluding Computers & Software	Excluding Electrical & Electronics	Including Category x Year FE
	(1)	(2)	(3)	(4)
	Dependent Variable is Log Patenting Growth. Estimations include Panel Fixed Effects			
Δ Log Immigration Quotas Estimator x Initial Immigrant Dependency by Technology	0.077	0.054	0.197	-0.005
	(0.113)	(0.107)	(0.115)	(0.093)
Δ Log Immigration Quotas Estimator x Initial Immigrant Dependency by Technology x Top 5 Cities for Breakthrough Inventions	0.275	0.274	0.220	0.275
	(0.157)	(0.144)	(0.196)	(0.115)
Linear Combination of Effects for Full Effect on Top 5 Cities	0.351	0.328	0.417	0.269
	(0.109)	(0.097)	(0.162)	(0.092)
Adjusted R-Squared	0.39	0.36	0.45	0.48
Observations	288	256	232	288

Notes: See Table 6. The core regressor is the expected immigrant invention nationally due to immigration quotas altered by the 1990 Act interacted with each technology's initial dependency on immigrant inventors.

Table 8: Placebo Estimators on Timing of 1990 Act

	Base Estimation	Forward Placebo Estimator	Lagged Placebo Estimator
	Dep. Variable is Log Patenting Growth Estimations include Panel Fixed Effects		
Δ Log Immigration Quotas Estimator x	0.351	0.359	0.348
Initial Immigrant Dependency by Technology	(0.109)	(0.112)	(0.109)
Placebo Estimator Five Years Earlier x		0.122	
Initial Immigrant Dependency by Technology		(0.165)	
Placebo Estimator Five Years Later x			-0.165
Initial Immigrant Dependency by Technology			(0.180)
Adjusted R-Squared	0.41	0.41	0.41
Observations	144	144	144

Notes: See Table 7. Placebo estimators that move the effective date of the 1990 Act forward or back five years. The panel is restricted to the top five cities only.

App. Table 1: Descriptive Statistics for Inventors Residing in US

	Ethnicity of Inventor								
	Anglo-Saxon	Chinese	European	Hispanic	Indian	Japanese	Korean	Russian	Vietnam.
	A. Ethnic Inventor Shares Estimated from US Inventor Records, 1975-2004								
1975-1979	74.8%	2.1%	15.6%	2.7%	2.0%	0.6%	0.3%	1.9%	0.1%
1980-1984	73.4%	2.9%	15.1%	2.7%	2.6%	0.7%	0.4%	2.0%	0.1%
1985-1989	72.2%	3.6%	14.6%	2.9%	3.1%	0.8%	0.5%	2.1%	0.2%
1990-1994	70.0%	4.8%	14.1%	3.2%	3.9%	0.9%	0.6%	2.2%	0.4%
1995-1999	66.4%	6.7%	13.6%	3.5%	5.2%	0.9%	0.7%	2.5%	0.5%
2000-2004	63.1%	8.8%	13.0%	3.8%	5.9%	1.0%	0.9%	2.8%	0.6%
Chemicals	65.8%	7.3%	14.4%	3.2%	4.9%	0.9%	0.7%	2.5%	0.3%
Computers	62.9%	8.4%	12.6%	3.4%	7.5%	1.0%	0.7%	2.7%	0.7%
Pharmaceuticals	64.8%	7.2%	14.8%	3.9%	4.6%	1.1%	0.8%	2.6%	0.3%
Electrical	64.3%	8.3%	13.3%	3.3%	5.3%	1.0%	0.9%	2.8%	0.7%
Mechanical	72.8%	3.3%	14.2%	3.3%	2.8%	0.7%	0.5%	2.2%	0.2%
Miscellaneous	74.1%	2.9%	13.9%	3.6%	2.3%	0.6%	0.5%	1.9%	0.2%
Top Cities as a	WS (84)	SF (14)	MIL (21)	MIA (16)	SF (8)	SD (2)	BAL (2)	NYC (4)	AUS (2)
Percentage of	SLC (83)	LA (8)	NOR (19)	SA (9)	AUS (7)	SF (2)	LA (1)	BOS (4)	SF (1)
City's Patents	NAS (82)	AUS (6)	STL (19)	WPB (6)	PRT (6)	LA (2)	DC (1)	HRT (4)	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), DC (Washington), HRT (Hartford), 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), SLC (Salt Lake City), 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); Anglo-Saxon provides a residual in the Census statistics. Many US inventors with European names are native citizens.

App. Table 2: Ethnic Inventor Contributions by City

	Total Invention Share			Anglo-Saxon and European			Immigrant Ethnicities			Chinese and Indian		
	1975-1984	1985-1994	1995-2004	1975-1984	1985-1994	1995-2004	1975-1984	1985-1994	1995-2004	1975-1984	1985-1994	1995-2004
Atlanta, GA	0.6%	1.0%	1.3%	0.6%	1.0%	1.4%	0.3%	0.7%	1.0%	0.3%	0.7%	1.0%
Austin, TX	0.4%	0.9%	1.8%	0.4%	0.9%	1.8%	0.4%	1.2%	2.0%	0.4%	1.5%	2.3%
Baltimore, MD	0.8%	0.8%	0.7%	0.8%	0.8%	0.7%	0.7%	0.7%	0.7%	0.5%	0.5%	0.6%
Boston, MA	3.6%	3.8%	3.9%	3.5%	3.7%	3.9%	3.8%	4.3%	3.9%	3.8%	4.0%	3.6%
Buffalo, NY	0.6%	0.5%	0.4%	0.6%	0.5%	0.4%	0.8%	0.6%	0.3%	1.1%	0.7%	0.3%
Charlotte, NC	0.3%	0.3%	0.3%	0.3%	0.4%	0.4%	0.1%	0.2%	0.2%	0.1%	0.2%	0.1%
Chicago, IL	6.0%	4.6%	3.5%	5.9%	4.6%	3.6%	6.7%	4.5%	3.3%	5.8%	4.0%	2.9%
Cincinnati, OH	1.0%	1.1%	1.0%	1.0%	1.2%	1.1%	0.7%	0.9%	0.7%	0.7%	1.0%	0.7%
Cleveland, OH	2.3%	1.7%	1.3%	2.3%	1.8%	1.5%	2.4%	1.5%	0.9%	2.6%	1.4%	0.8%
Columbus, OH	0.7%	0.5%	0.5%	0.7%	0.5%	0.5%	0.7%	0.6%	0.4%	0.8%	0.7%	0.3%
Dallas-Fort Worth, TX	1.6%	2.0%	2.3%	1.6%	2.0%	2.2%	1.2%	2.3%	2.6%	1.4%	2.3%	2.9%
Denver, CO	1.1%	1.2%	1.3%	1.1%	1.2%	1.5%	0.8%	1.0%	0.7%	0.7%	1.0%	0.6%
Detroit, MI	3.1%	3.3%	2.9%	3.1%	3.3%	3.0%	3.1%	3.0%	2.5%	3.2%	2.7%	2.5%
Greensboro-W.S., NC	0.2%	0.3%	0.3%	0.2%	0.4%	0.4%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
Hartford, CT	0.9%	0.9%	0.6%	0.9%	0.9%	0.6%	0.8%	0.7%	0.5%	0.8%	0.5%	0.3%
Houston, TX	2.3%	2.5%	1.9%	2.3%	2.5%	1.9%	1.9%	2.5%	1.9%	2.2%	2.8%	1.8%
Indianapolis, IN	0.8%	0.7%	0.7%	0.8%	0.7%	0.7%	0.7%	0.4%	0.4%	0.8%	0.5%	0.4%
Jacksonville, NC	0.1%	0.1%	0.1%	0.1%	0.1%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
Kansas City, MO	0.4%	0.3%	0.4%	0.4%	0.4%	0.4%	0.2%	0.1%	0.2%	0.2%	0.1%	0.2%
Las Vegas, NV	0.1%	0.1%	0.2%	0.1%	0.1%	0.2%	0.0%	0.1%	0.1%	0.0%	0.0%	0.1%
Los Angeles, CA	6.6%	6.1%	6.0%	6.4%	5.8%	5.3%	8.4%	8.1%	8.6%	6.5%	7.0%	7.6%
Memphis, TN	0.1%	0.2%	0.2%	0.1%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
Miami, FL	0.8%	0.9%	0.7%	0.7%	0.8%	0.6%	1.3%	1.4%	1.0%	0.6%	0.6%	0.4%
Milwaukee, WI	1.0%	0.9%	0.8%	1.0%	1.0%	0.9%	0.6%	0.6%	0.5%	0.4%	0.4%	0.5%
Minneap.-St. Paul, MN	1.9%	2.4%	2.6%	2.0%	2.6%	2.9%	1.5%	1.7%	1.6%	1.5%	1.8%	1.7%

App. Table 2: Ethnic Inventor Contributions by City, continued

	Total Invention Share			Anglo-Saxon and European			Immigrant Ethnicities			Chinese and Indian		
	1975-1984	1985-1994	1995-2004	1975-1984	1985-1994	1995-2004	1975-1984	1985-1994	1995-2004	1975-1984	1985-1994	1995-2004
Nashville, TN	0.1%	0.2%	0.2%	0.1%	0.2%	0.2%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%
New Orleans, LA	0.3%	0.2%	0.2%	0.3%	0.2%	0.2%	0.2%	0.2%	0.1%	0.2%	0.1%	0.1%
New York, NY	11.5%	8.9%	7.4%	10.9%	8.3%	6.7%	16.4%	12.9%	10.0%	17.3%	13.4%	9.7%
Norfolk-VA Beach, VA	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.2%	0.1%	0.1%
Orlando, FL	0.2%	0.3%	0.3%	0.2%	0.3%	0.3%	0.1%	0.2%	0.3%	0.1%	0.2%	0.4%
Philadelphia, PA	4.6%	4.0%	2.7%	4.5%	3.8%	2.7%	5.5%	5.0%	2.7%	6.2%	5.8%	2.8%
Phoenix, AZ	1.0%	1.2%	1.4%	1.0%	1.2%	1.4%	0.6%	1.2%	1.3%	0.4%	1.0%	1.4%
Pittsburgh, PA	1.9%	1.3%	0.8%	1.9%	1.3%	0.8%	2.2%	1.4%	0.6%	2.2%	1.3%	0.5%
Portland, OR	0.5%	0.8%	1.4%	0.5%	0.8%	1.4%	0.3%	0.5%	1.5%	0.2%	0.6%	1.6%
Providence, RI	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.4%	0.3%	0.2%	0.4%	0.2%
Raleigh-Durham, NC	0.3%	0.6%	1.1%	0.3%	0.6%	1.1%	0.3%	0.7%	1.0%	0.3%	0.8%	1.0%
Richmond, VA	0.3%	0.3%	0.2%	0.3%	0.3%	0.2%	0.3%	0.3%	0.2%	0.3%	0.3%	0.2%
Sacramento, CA	0.2%	0.4%	0.5%	0.2%	0.4%	0.5%	0.2%	0.4%	0.5%	0.2%	0.3%	0.5%
Salt Lake City, UT	0.4%	0.5%	0.6%	0.4%	0.6%	0.6%	0.2%	0.3%	0.3%	0.2%	0.3%	0.3%
San Antonio, TX	0.1%	0.2%	0.2%	0.1%	0.2%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%
San Diego, CA	1.1%	1.6%	2.2%	1.1%	1.6%	2.1%	1.0%	1.6%	2.6%	0.8%	1.3%	2.4%
San Francisco, CA	4.8%	6.6%	12.2%	4.6%	5.9%	9.6%	7.0%	10.8%	21.8%	8.3%	13.0%	25.7%
Seattle, WA	0.9%	1.3%	1.9%	1.0%	1.3%	2.0%	0.7%	1.0%	1.8%	0.6%	1.0%	1.8%
St. Louis, MO	1.0%	0.9%	0.8%	1.1%	1.0%	0.9%	0.8%	0.6%	0.4%	1.0%	0.8%	0.4%
Tallahassee, FL	0.4%	0.5%	0.4%	0.4%	0.5%	0.5%	0.3%	0.4%	0.3%	0.2%	0.2%	0.2%
Washington, DC	1.5%	1.5%	1.4%	1.5%	1.4%	1.4%	1.7%	1.8%	1.5%	1.6%	1.7%	1.6%
West Palm Beach, FL	0.3%	0.5%	0.4%	0.3%	0.5%	0.5%	0.2%	0.5%	0.4%	0.3%	0.3%	0.2%
Other 234 Major Cities	21.8%	22.3%	20.7%	22.2%	23.1%	22.3%	18.3%	17.5%	14.7%	19.2%	18.2%	14.4%
Not in a Major City	9.0%	8.2%	6.6%	9.4%	8.8%	7.6%	5.7%	4.4%	3.1%	5.1%	3.8%	2.4%

Notes: Table documents the spatial distribution of patenting across cities and time periods. The shares in each column sum to 100%. Immigrant Ethnicities in the third triplet include Chinese, Indian, Hispanic, Japanese, Korean, Russian, and Vietnamese contributions.

App. Table 3: Migration Patterns in Census of Populations, 1980-2000

	Total Workforce				Bachelor's Educated Scientists & Engineers			
	1980	1990	2000	Mean	1980	1990	2000	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Share Who Moved States or Immigrated in Previous Five Years by Immigration Status							
Overall	12%	12%	12%	12%	25%	23%	23%	24%
US Natives	11%	10%	10%	10%	23%	21%	18%	20%
Immigrants	26%	23%	24%	24%	38%	33%	42%	38%
Immigrants, Chinese and Indian	40%	30%	33%	34%	45%	33%	51%	43%
	B. Restricting Panel A to Internal Migration of Workers Aged 35 and Older							
Overall	7%	7%	7%	7%	14%	13%	12%	13%
US Natives	7%	7%	7%	7%	13%	13%	11%	12%
Immigrants	7%	7%	8%	8%	19%	15%	15%	16%
Immigrants, Chinese and Indian	17%	10%	12%	13%	29%	16%	21%	22%
	C. Composition of Total Moves in Panel A							
Natives	84%	79%	71%	78%	81%	78%	58%	72%
Immigrants, Previous Five Years	10%	12%	17%	13%	8%	10%	25%	14%
Immigrants, Earlier	7%	9%	12%	9%	11%	12%	17%	13%

Notes: Table documents mobility patterns from the 1980-2000 Census of Populations 5% State samples. The total workforce is defined as workers aged 25 to 55, employed in non-military jobs, living outside of group quarters, and working more than 40 weeks per year and 30 hours per week. Bachelor's educated scientists and engineers are further designated through occupation titles and reported degree attainment. Immigration status and source country are designated through country of birth. Panel A documents the percentage of each worker type who is new to his or her state of residence from five years earlier. This includes internal migration and recent immigration to the US. Panel B further restricts the sample to workers aged 35 to 55 and residing in the US for five years or longer at the time of the Census (removing recent immigration). Panel C documents the composition of all workers new to the state from five years earlier. Care should be exercised when comparing across Censuses as some definitions can change (especially the occupation definition in the 2000 Census).

App. Table 4: Disaggregated Interactions for Chinese/Indian and Other Ethnic Dependencies

	Log Patent Growth		Log Patent Growth
Δ Log Chinese/Indian Patenting x Initial Chinese/Indian Dependency by Technology	0.079 (0.099)	Δ Log Immigration Quotas Estimator x Initial Chinese/Indian Dependency by Technology	0.091 (0.116)
Δ Log Chinese/Indian Patenting x Initial Chinese/Indian Dependency by Technology x Top 5 Cities for Breakthrough Inventions	0.181 (0.174)	Δ Log Immigration Quotas Estimator x Initial Chinese/Indian Dependency by Technology x Top 5 Cities for Breakthrough Inventions	0.208 (0.193)
Δ Log Other Ethnic Patenting x Initial Other Ethnic Dependency by Technology	-0.017 (0.157)	Δ Log Immigration Quotas Estimator x Initial Other Ethnic Dependency by Technology	-0.017 (0.107)
Δ Log Other Ethnic Patenting x Initial Other Ethnic Dependency by Technology Top 5 Cities for Breakthrough Inventions	0.177 (0.280)	Δ Log Immigration Quotas Estimator x Initial Other Ethnic Dependency by Technology Top 5 Cities for Breakthrough Inventions	0.102 (0.202)
Linear Combination of Effects for Chinese/Indian Interaction Effect on Top 5 Cities	0.260 (0.143)	Linear Combination of Effects for Chinese/Indian Interaction Effect on Top 5 Cities	0.299 (0.155)
Linear Combination of Effects for Other Ethnic Interaction Effect on Top 5 Cities	0.161 (0.232)	Linear Combination of Effects for Other Ethnic Interaction Effect on Top 5 Cities	0.084 (0.171)
Cross-Sectional and Year Fixed Effects	Yes	Cross-Sectional and Year Fixed Effects	Yes
Adjusted R-Squared	0.39	Adjusted R-Squared	0.39
Observations	288	Observations	288

Notes: See Tables 6 and 7. Table disaggregates non-Anglo-Saxon and European ethnicities into Chinese and Indian ethnicities and other ethnicities. Other Ethnic patenting includes Hispanic, Japanese, Korean, Russian, and Vietnamese contributions.