How Much Does Immigration Boost Innovation? *

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Abstract

We measure the extent to which skilled immigrants increase innovation in the United States by exploring individual patenting behavior as well as state–level determinants of patenting. The 2003 National Survey of College Graduates shows that immigrants patent at double the native rate, and that this is entirely accounted for by their disproportionately holding degrees in science and engineering. These data imply that a one percentage point rise in the share of immigrant college graduates in the population increases patents per capita by 6%. This could be an overestimate of immigration's benefit if immigrant inventors crowd out native inventors, or an underestimate if immigrants have positive spill–overs on inventors. Using a 1940–2000 state panel, we show that immigrants do have positive spill–overs, resulting in an increase in patents per capita of 9–18% in response to a one percentage point increase in immigrant college graduates. We isolate the causal effect by instrumenting the change in the share of skilled immigrants in a state with the state's predicted increase in the share of skilled immigrants. We base the latter on the 1940 distribution across states of immigrants from various source regions and the subsequent national increase in skilled immigrants from these regions.

Economists have studied the impact of immigration on a variety of host country outcomes. For example, Card (2007) considers U.S. immigration's impact on population growth, skill composition, internal migration, wages, rents, taxes and the ethnic and income composition of neighborhoods and schools. In contrast, the impact of immigration on innovation has received less attention. In addition to the direct contributions of immigrants to research, immigration could boost innovation indirectly through positive spill–overs on fellow researchers, the achievement of critical mass in specialized research areas, and the provision of complementary skills such as management and entrepreneurship. Some tantalizing facts hint at the possible importance of these effects for the United States. Compared to a foreign–born population of 12% in 2000, 26% of U.S.–based Nobel Prize recipients from 1990–2000 were immigrants (Peri 2007), as were 25% of founders of public venture–backed U.S. companies in 1990–2005 (Anderson and Platzer 2006), and founders of 25% of new high–tech companies with more than one million dollars in sales in 2006 (Wadhwa et al. 2007). Immigrants are over–represented among members of the National Academy of Sciences and the National Academy of Engineering, among authors of highly–cited science and engineering journal articles, and among founders of bio–tech companies undergoing IPOs (Stephan and Levin 2001). Kerr (2007) documents the surge in the share of U.S. patents awarded to U.S.–based inventors with Chinese and Indian names to 12% of the total by 2004, and Wadhwa et al. (2007) find that non–U.S. citizens account for 24% of international patent applications from the United States.

The goal of our paper is to assess the impact of skilled immigration on innovation as measured by U.S. patents per capita. The purpose of studying patents is to gain insight into technological progress, a driver of productivity growth and ultimately economic growth. If immigrants increase patents per capita, they may increase output per capita and make natives better off. This is an important consideration for the debate concerning how many and what type of immigrants should be admitted to the United States, and particularly for the discussion of the appropriate number of employer–sponsored H–1B visas for skilled (especially science and engineering) workers. The context of the discussion is the shift from European to low and middle–income source countries since the

Immigration Act of 1965, and the concomitant faster increase in unskilled immigration than skilled immigration.

One way skilled immigrants could increase patenting per capita is through a greater concentration than natives in science and engineering occupations. Immigrants are likely to be over–represented in such occupations, since scientific and engineering knowledge transfers easily across countries: it does not rely on institutional or cultural knowledge, is not associated with occupations with strict licensing requirements like medicine, and does not require the sophisticated language skills of a field like law.[1] Skilled immigrants could also increase patenting per capita if a combination of immigration policies and immigrant self–selection leads them to be more educated or of higher unobserved inventive ability. Even immigrants who do not patent themselves may increase patenting by providing complementary skills to inventors, such as entrepreneurship. Immigrant inventors may in turn make natives more inventive. Conversely, immigrant inventors' contributions could be offset by negative spill–overs, for example, if their presence discourages natives from working in science and engineering.[2]

After establishing theoretical propositions concerning the decision of scientists and engineers to emigrate, we begin our empirical analysis by examining how much immigrants patent using the 2003 National Survey of College Graduates (NSCG), which contains information on both patenting activity and birth place. The individual–level data allow us to gauge the impact of immigrants on patents per capita under the assumption that immigrants do not influence the behavior of natives or other immigrants, and allow us to examine whether immigrants patent more than natives because they have higher inventive ability or merely different education or occupations.

In order to account for immigrants' possible influence on natives or other immigrants, we turn to a panel of U.S. states from 1940–2000, based on data from the U.S. Patent and Trademark Office, the decennial censuses and other sources. We provide estimates

[1] See Chiswick and Taengnoi (2007) and Peri and Sparber (2008) for evidence.

[2] In the most relevant paper, Borjas (2006) finds that immigrants do not crowd out natives as a whole from graduate school.

of skilled immigrants' impact on patents per capita that encompass both immigrants' own patenting and any positive or negative spill–overs immigrants might have. To obtain the causal effect of immigrants despite their endogenous choice of destination state, we difference the data across census years, and instrument the change in the share of skilled immigrants in a state with the state's predicted increase in the share of skilled immigrants. We base the latter on the 1940 distribution across states of immigrants from various source regions and the subsequent national increase in skilled immigrants from these regions.

We contribute to two understudied areas, the impact of immigration on innovation and the individual determinants of innovation, as well as to the study of the regional determinants of innovation. Our work is also relevant for the macroeconomic growth literature, where the link between innovation and the number of researchers is the key to growth.[3]

We go beyond the most closely related paper linking immigration and innovation, Peri (2007), by adding individual–level analysis, extending the state panel, using instrumental variables to correct for endogeneity, and defining skilled immigration more broadly and consistently across time. These considerations also distinguish our paper from the time–series analysis of Chellaraj, Maskus and Mattoo (2008). Both of these papers find skilled immigration increases U.S. patenting. Our analysis is more general than that of Stuen, Mobarak and Maskus (2007) and Kerr and Lincoln (2008). The former authors find that immigrant students increase U.S. university patenting and science and engineering publishing. The latter authors find that when the national population of H–1B visa–holders increases, patenting by inventors with Indian and Chinese names rises in states that have many H–1B applications. A related paper by Niebuhr (2006) concludes that German regions with more diverse worker nationalities (as measured by the Herfindahl index) patent more. The result is not robust to region fixed effects, however, no doubt in part because she has only two years of data close in time (1997 and 1999). Paserman (2008) finds no effect of skilled immigration on Israeli manufacturing productivity. We are not aware of previous papers with regression analysis of the individual determinants of

[3] Aghion and Howitt (1992), Grossman and Helpman (1991a,b), Jones (1995), Romer (1990).

patenting, though Morgan, Kruytbosch and Kannankutty (2003) note in passing the immigrant advantage in patenting in the 1995 NSCG, and economic historians have studied the characteristics of nineteenth century inventors (e.g. Khan and Sokoloff 1993).

There is a large literature on the regional determinants of patenting, but the analysis relies primarily on cross–section variation or qualitative analysis. The literature considers the effects of private and public R&D spending, the presence of a university, the presence of small firms, the competitiveness of product markets, the presence of an airport, geographic centrality, population density and size and the presence of skilled workers, especially scientists and engineers.[4] The most closely related paper is by Zucker and Darby (2006): they pool data on Bureau of Economic Analysis regions for 1981–2004, and find that non–university patenting is affected by neither the presence of star scientists, a high wage (proxying for education) nor a high stock of relevant journal publications (representing the stock of knowledge).[5]

Our theoretical analysis shows that workers with science and engineering education are more likely to emigrate than other ("professional") skilled workers if the expected wage premium commanded by professional over unskilled jobs in the destination is smaller than the cost of adapting professional skills to the destination institutions. We demonstrate this in Appendix A. Our empirical analysis of the NSCG data shows that immigrants account for 24% of patents, twice their share in the population, and that the skilled immigrant patenting advantage over skilled natives is entirely accounted for by immigrants' disproportionately holding degrees in science and engineering fields. The data imply that a one percentage point increase in college–graduate immigrants' share of the population increases patents per capita by 6%.

[4] See, for example, Acs (2002), Bottazzi and Peri (2003), Hicks et al. (2001), and the papers in Acs et al. (2002); Jaffe, Trajtenberg and Henderson (1993) and successor papers study geographic patterns of patent citations.

[5] Other relevant papers include Agrawal, Kapur and McHale (2002), who find that emigration from India reduces access to knowledge in India, Zucker et al. (2006), who examine the determinants of a region's publications in nanotechnology, and Marx, Strumsky and Fleming (2007) and Stuart and Sorenson (2003), who examine the effect of a state's enforcing non–compete laws on inventor inter–firm mobility and biotech IPOs respectively.

This could overestimate the contribution of immigrants, if immigrants crowd out natives from science and engineering, or could underestimate the contribution, if immigrants have positive spill–overs. The state panel analysis, which estimates the contribution including any spill–overs, shows evidence of positive spill–overs of immigrants, since the estimates of their impact on patents per capita are higher than in the NSCG: a one percentage point rise in the share of immigrant college graduates in the population increases patents per capita by 9–18%. The state–level results mean that the 1990–2000 increase in the population share of this group from 2.2% to 3.5% increased patents per capita by 12–21% in a period when patents per capita rose 63%. We find that immigrants who are scientists and engineers or who have post–college education boost patents per capita more than immigrant college graduates.

1 Empirical methodology

We use individual–level data to measure and explain differences in patenting behavior between immigrants and natives, and to gauge the contribution of immigrants to patenting per capita under the assumption that immigrants do not affect the behavior of natives or other immigrants. We then use state–level data to estimate the effect of immigrants on patenting per capita, including any positive or negative spill–overs.

1.1 Individual–level data

A measure of the increase in patenting per capita owing to skilled immigrants can be calculated as follows.[6] Let the skilled immigrant share of patents be α_0 (we obtain this value from the NSCG) and the skilled immigrant share of the population be α_1 (we obtain this value from the census). Let M^S be the number of skilled immigrants and P^{MS} their patents. If the skilled immigrant share of the population increases by one percentage point, the percent increase in skilled immigrants is $\frac{\Delta M^S}{M^S} = \frac{1}{\alpha_1}\frac{0.01}{0.99-\alpha_1}$, the percent increase in the population is $\frac{\Delta M^S}{POP} = \frac{0.01}{0.99-\alpha_1}$ and the percent increase in patents

[6] The full algebra is presented in Appendix B.

is $\frac{\Delta P^{MS}}{P} = \frac{1}{P}\frac{P^{MS}}{M^S}\Delta M^S = \alpha_0 \frac{\Delta M^S}{M^S}$. The percent increase in patents per capita is therefore

$$\frac{1+\frac{\Delta P^{MS}}{P}}{1+\frac{\Delta M^S}{POP}} - 1 = (0.01)\frac{\alpha_0 - \alpha_1}{\alpha_1(1-\alpha_1)}. \tag{1}$$

We shall establish below that skilled immigrants patent more than skilled natives, and that this difference is driven by the difference in patenting at all. For policy–makers contemplating reducing skilled immigration and inducing more natives to study science and engineering, it may be interesting to understand the reasons for the immigrant advantage. To explore these reasons, we estimate a probit for the probability of having a patent granted, or the probability of commercializing or licensing a patent, weighted by the survey weights:

$$P(patent_j) = \beta_0 + \beta_1 IM_j + X_j\beta_2 + \epsilon_j, \tag{2}$$

where j indexes individuals and IM is a dummy for the foreign–born. The coefficient of interest is β_1. We are interested in how much of the raw patenting gap between immigrants and natives (the value of β_1 with no X covariates) can be explained by adding the covariates X: field of study of the highest degree, the highest degree, and demographic variables. We perform the regressions for three samples: college graduates, post–college degree holders, and scientists and engineers.

1.2 State–level data

We supplement the analysis using a panel of U.S. states with decennial data from 1940–2000. By extending the period of observation back to 1940, we are able to distinguish long run and short run effects by differencing the data in lengths varying from ten to 50 years.[7] We estimate

$$\Delta log\ \frac{P_{i,t+1}}{POP_{i,t+1}} = \gamma_0 + \gamma_1 \Delta I^S_{it} + \gamma_2 \Delta N^S_{it} + \Delta X_{it}\gamma_3 + Z_{i,1940}\gamma_4 + \mu_t + \Delta\eta_{it}, \tag{3}$$

where i indexes states, P is the number of patents, POP is state population, I^S is the share of the population or workforce (18–65) composed of skilled immigrants, N^S represents the

[7]Strictly speaking, we should refer to low–frequency and high–frequency effects.

corresponding share for skilled natives, $Z_{i,1940}$ are characteristics of the state in 1940, X are contemporaneous state characteristics and μ_t are year dummies. The coefficient of interest is γ_1, though its size relative to γ_2 is also of interest. We also present results from specifications where the dependent variable is not in logs.[8]

We define a skilled person variously as one with a college degree or more, one with post–college education, or one working in a science, engineering or computer science occupation. We include characteristics of the state in 1940 (including land area), to capture the convergence in patents per capita occurring over the time period. The X covariates comprise the log of defense procurement spending and the log of the average age of state residents (18–65). We deliberately do not include R&D spending, as we believe this to instead be a potential outcome variable. We lead the dependent variable by one year to allow for a year of research time between the change in the inputs and the patent application, as anecdotal evidence suggests the lag can vary between a few months and two years.

There were several major changes to the patent system between 1980 and 1998 (see Hall 2005). One change led to a large increase in patenting in electrical engineering relative to other sectors. To capture potentially differential effects of this by state, we include among the X's the share of employment in electrical engineering–related sectors in 1980, interacted with year dummies.[9] Alternatively, we capture this by controlling for region–specific dummies interacted with a dummy for differences involving years beyond 1980.

We use state populations to weight the regressions,[10] since in some small states one company drives the time series of patenting,[11] and we cluster standard errors by state to allow for serial correlation. Because we account for state fixed effects by estimating

[8]All patents are filed in Washington D.C.; they are attributed to states based on the home address of the first inventor.

[9]We use 1980 values as electrical engineering employment was still tiny in most states in 1940–1970.

[10]Specifically, we weight by $1/(1/pop_{i,t+1} + 1/pop_{i,t-k+1})$, where k is the length of the difference.

[11]Idaho's emergence as the state with most patents per capita has been driven by one semi–conductor company, Micron Technology Inc., founded in 1978, which was granted 1643 patents in 2001 and was the fourth–ranked company in this regard.

equations differenced across time, we elect not to include the change in the patent stock among the regressors as would be suggested by patent models. Furthermore, because we analyze long–run changes, we have chosen not to use a partial adjustment model.[12]

Equation (3) suffers from an endogeneity problem. Skilled workers are likely to migrate to states which are growing or innovating, causing $\hat{\gamma}_1$ and $\hat{\gamma}_2$ to be biased upward in least squares estimation. On the other hand, $\hat{\gamma}_1$ in particular could be biased towards zero owing to measurement error.[13] We devise an instrument to address these problems for skilled immigrants, inspired by a shift–share type analysis of the change in popularity of a state stemming from changes in the origin regions of skilled immigrants at the national level.[14] To illustrate, if immigrants from Europe prefer the northeastern United States because it is closer to home and because other Europeans are already there because of geography, and Asian immigrants prefer the west coast for the same reasons, the large national increase in the share of skilled immigrants that are Asian will lead to an increase in skilled immigration to the west coast relative to the northeast. If the national increase in skilled Asian immigrants is caused by the change in U.S. immigration policy in 1965, the opening of China to the world in 1979, along with increases in tertiary education in China and India, it is orthogonal to shocks to west coast patenting.

For a state i, the predicted change in the number of skilled immigrants, caused by changing origin regions k, can be written as

$$\Delta \hat{M}_i^S = \sum_k \frac{M_{ik}}{M_k} \Delta M_k^S = \sum_k \lambda_{ik} \Delta M_k^S,$$

where λ_{ik} is state i's share in 1940 of the national total of immigrants who originate

[12]We have estimated these models. The coefficient on the change in the stock of patents is close to one, rendering all other coefficients insignificant, while the coefficient on the partial adjustment term is insignificant.

[13]There is considerable measurement error for small states in the 1950 census, which was a smaller sample than later years and which asked certain key questions of only one quarter of the sample. There is also measurement error for the share of immigrant post–college and immigrant scientists and engineers in small states in the 1940–70 censuses.

[14]This instrument is similar to the instrument developed by Card (2001). For ΔN^S, the change in the share of native skilled workers, we have experimented unsuccessfully with lagged college enrollments as an instrument. The enrollment data only begin in the 1970s.

from region k, and ΔM_k^S is the national change in the number of skilled immigrants from that region. We use 18 source regions or countries, listed in Appendix Table 1. Because the variable to be instrumented, ΔI_{it}^S, is a percentage point change, we convert $\Delta \hat{M}_i^S$ to percentage points by dividing by the population level at the start of the period to which Δ refers, to define our final instrument as:

$$\frac{\Delta \hat{M}_i^S}{POP_i}.$$

We deliberately base the λ_{ik} on immigrants of all educations (and ages) to emphasize the role of geography and taste and minimize the role of economic factors that might attract skilled workers specifically. We can control for the λ_{ik} in the regressions, to ensure that the instrument is not correlated with the error term due to their omission, and the year dummies control for all national trends. If controlling for λ_{ik} and the other covariates does not account for state–specific patenting shocks which are very persistent and influence national inflows of particular immigrant groups (e.g. California has serially correlated positive patenting shocks which caused low–skill Chinese to settle there before 1940 and which incited skilled Chinese to move to the United States in more recent years), the instrument could be correlated with the error term. We present evidence below that suggests this is not the case.

Information on Alaska and Hawaii is not available until 1960. If the instrument is constructed using the 1960 shares for Alaska and Hawaii instead of the missing 1940 shares, Hawaii is such an outlier (due to its high share of Asian immigrants in 1960) that the instrument does not statistically significantly predict immigration patterns even in weighted regressions. We therefore drop Hawaii from the analysis entirely, and for simplicity drop Alaska as well. This makes an imperceptible difference to weighted least squares regressions, and only a small difference to the less preferred unweighted regressions.

2 Data and Descriptive Statistics

2.1 Individual–level data

We use the individual–level data from the 2003 National Survey of College Graduates (NSCG). These data are a stratified random sample of people reporting having a bachelor's degree or higher on the long form of the 2000 census. In 2003, all respondents who had ever worked were asked whether they had applied for a U.S. patent since October 1998, whether they had been granted any U.S. patent since October 1998, and if so, how many, and how many had been commercialized or licensed.[15] The survey will not capture patents by those with less than a college degree, but we assume that most patents are captured. Appendix C provides more information on the NSCG. We include in our sample respondents 65 or younger (the youngest respondent is 23, but few are younger than 26). Immigrants are those born outside the United States.

We define three (not mutually exclusive) skill categories, motivated in part by consistency with categories that can be distinguished in the censuses: college graduates (i.e. the full sample); holders of a post–college degree; and those working as scientists and engineers in the survey week. Only 51% of respondents who had been granted a patent reported working in a science or engineering occupation. Another 18% reported a management occupation: a research team's manager is sometimes listed as a co–inventor on a patent, and all inventors listed are captured in the data; also, many inventors will have been promoted to management since obtaining a patent. Science and engineering technicians represent 2.5% of patent holders, and respondents in health–related occupations represent another 3.0%.

Table 1 shows details of how patenting varies by immigrant status for the three skill groups. For college graduates (the whole sample, columns 1–2), 1.9% of immigrants were granted patents compared to 0.9% of natives, a ratio of 2.1, and patents per capita were

[15] Questions on patents were also asked in the 1995 NSCG, but only of respondents who said they worked in research and development in the survey week, which will cause the patents of job changers to be missed.

0.057 for immigrants and 0.028 for natives, a ratio of 2.0. Immigrants therefore patent at about twice the native rate, with the difference being principally in the probability of patenting at all. Immigrants held a slightly smaller advantage in patents commercialized or licensed, patents likely to benefit society more than others: 1.2% immigrants had commercialized a patent compared to 0.6% for natives, but commercialized patents per capita were 0.029 for immigrants and 0.017 for natives. The immigrant–native gap is larger for the sample with post–college education (columns 3–4), but much smaller for the sample working in science and engineering occupations (columns 5–6). For example, 6.2% immigrants in the latter sample had been granted a patent, compared to 4.9% natives, and immigrants hold 1.35 times the patents per capita of natives. Appendix Table 2 contains the means of variables used in the regression analysis below.

2.2 State–level data

The patent data used in the state–level analysis come from the U.S. Patent and Trademark Office (USPTO). Patents are attributed to states based on the home address of the first inventor on the patent. We merge a series based on electronic data from 1963 onwards with a series from paper records for 1883–1976 (see Appendix C for the merging procedure). Patents are classified according to application (filing) date. Figure 1 shows the evolution of total patents and patents per 100,000 residents from 1941-2001, our study period.

In Figure 2 we use patent data from 1929 to 2001 to display the long–run convergence across states in patenting, as measured by changes in the (unweighted) standard deviation of log patents. The convergence in patents, shown by the downward slope of the top line, is not merely a function of convergence in population, as is demonstrated by the convergence in patents per capita (bottom line).[16] However, there is divergence in patents per capita from 1990–2001, and there have historically been other periods of divergence. California is a force for divergence, as may be seen by the growing gap between the inequality of state patent counts with California (top line) and without California (middle line).

[16]Papers such as Co et al. (2006) have previously noted cross–state convergence in patents per capita.

We have also used an extract from the Harvard Business School patent data file, which contains information on patents granted from 1975 to 2007, arranged by year of application and patent class.[17] We have aggregated the patent classes to six categories using the classification of Hall, Jaffe and Trajtenberg (2001) and our own classification of patent classes created since 1999. The extract contains the number of citations made to patents in each patent class, state and application year. These may be viewed as a proxy for the quality of the patent. We analyze 1971–2001 data using this extract (see Appendix C for how we approximate 1971 values).

To compute the shares of the population in various education and occupation classes, to divide these into immigrant and native, and to calculate the average age of the state's population, we use the IPUMS microdata of the decennial censuses. Post–college education is the highest education level that can be measured consistently throughout 1940–2000. We define immigrants to be the foreign born. Information for Alaska and Hawaii is not available in 1940 and 1950, and we elect to drop these states entirely for reasons explained in the methodology section.

The variable means for the full 1940–2000 sample, weighted by population, are reported in Table 2. Between 1940 and 2000, the share of the population 18–65 composed of immigrants with college education or more increased twelvefold to 3.5%, while the equivalent share for post–college increased twelvefold to 1.6%. The population shares comprising natives with at least college and with post–college increased from 4.1% to 20.0% and from 1.1% to 7.7% respectively. The share of workers composed of immigrant scientists and engineers multiplied elevenfold to 0.9%, while the native share rose from 0.6% to 3.5%. The Appendix Table 2 contains information about the variables used in the construction of the instruments.

[17] We are very grateful to Bill Kerr for making this extract for us.

3 Results

3.1 Individual determinants of patenting

The NSCG data may be used to estimate the direct effect of immigration on patenting, ignoring possible crowd–out or spill–over effects, using equation (1). Immigrants hold 24.2% of patents in the (weighted) data ($\alpha_0 = 0.242$), and in the 2000 census (the basis of the NSCG sampling frame), college–graduate immigrants were 3.5% of the U.S. population ($\alpha_1 = 0.035$). A one percentage point rise in the share of college immigrants in the population therefore implies an increase in patents per capita of 0.061, or 6.1%. The same exercise may be performed for natives, with the result that a one percentage point rise in the share of college natives increases patents per capita by 3.5%. As immigrants with post–college education have 2.0 (=0.112/0.057) times as many patents per capita as immigrants with only a college degree (see Table 1), the direct impact of an extra percentage point of post–college immigrants in the population is likely to be 2.0 times higher, or an extra $2.0 \times 6.1 = 12.2\%$. Similarly, the contribution of an additional percentage point immigrant scientists and engineers is likely to be $3.1 \times 6.1 = 18.9\%$.

To assess the reasons for the immigrant patenting advantage, we first observe that in Table 1 immigrants' patenting advantage over natives is much smaller in the scientist and engineer sample (columns 5 and 6) than in the overall sample (columns 1 and 2). This suggests that immigrants' advantage is due in large part to a greater science and engineering orientation. Table 3 lends further support to this. Column 1 shows that, for the whole sample, 6.6% of those with a highest degree in physical science and 6.1% of those with a highest degree in engineering had patented, far ahead of other fields. Column 2 shows a qualitatively similar picture for commercialized or licensed patents. Immigrants' education is therefore well–suited to patenting, since columns 3 and 4 show that the share of immigrants with physical science and engineering degrees is more than twice as high as for natives.

In Table 4, we pursue this explanation using the probit of equation (2) for the probability of patenting. Column 1 shows that immigrants are 1.0 percentage points more likely to have been granted a patent in the sample of college graduates (top panel), 2.3 percentage points more likely in the sample of post–college educated (second panel) and 1.3 percentage points more likely in the sample of scientists and engineers (third panel). In the second column, we control for the field of study of the highest degree obtained by the respondent by adding 30 dummies. For all three samples, the gap becomes small: 6–9% of the original size for college and post–college graduates, and 24% for scientists and engineers. In the third column, we control for the highest degree obtained by the respondent. For college graduates and scientists and engineers, the direction of the gap is reversed: immigrant scientists and engineers are a statistically significant 0.95 percentage points less likely to patent than natives. Controlling for age, age squared, sex and current employment status in column 4 changes little. Skilled immigrants' advantage is therefore entirely due to the nature of their education, and not to any selection on unobservables such as ability.[18] In columns 5 and 6 we show that the same conclusions may be drawn for the probability of commercializing or licensing a patent.

3.2 State determinants of patenting

In Table 5, we estimate the state determinants of log patenting per capita using differences of varying lengths, with a college degree as the measure of skill and least squares estimation of equation (3). The regression in column 1 is unweighted, while those in the other columns are weighted. A ten–year difference is taken in columns 1 and 2, a thirty–year difference in column 3 and a fifty year difference in column 4. The coefficients on the changes in the immigrant college shares are positive and significant. A one percentage point increase in the share of the population composed of immigrant college graduates is associated with a 12–15% increase in patenting per capita. These effects are larger than the 6% impact calculated based on the NSCG data, implying positive spill–over effects of immigrants.

The coefficients on the change in the share of native college graduates are smaller than the coefficients for immigrants. The point estimate increases as the difference length

[18]It is possible that unobservable effects cancel out e.g. immigrants may have higher ability but lower quality education.

increases, and for 50–year differences the coefficient is a significant 5.8 in column 4. The immigrant/native ratio is 2.6, somewhat larger than the 1.9 ratio in the NSCG. The coefficient suggests that skilled natives too have positive spill–overs, as the effect of a one percentage point increase in their population share based on the NSCG data was 3.5%. The absence of significance at short differences probably reflects the emphasis of short differences on high–frequency events (Baker, Benjamin and Stanger 1999), since the share of native college graduates changes only gradually.

Older populations appear to be more innovative, as indicated by the positive coefficients on the average age of the state. This may reflect the importance of management or other skills complementary to innovation. As suggested by time series work in Griliches (1990), Department of Defense procurement spending lowers patenting, presumably in part because military invention is primarily protected by secrecy rather than patents. Finally, the importance of the 1940 conditions (and land area) increases with the difference length, and the coefficients indicate that patent growth was lower for initially richer and more densely populated states.

We reproduce key Table 5 results in Table 6 Panel A columns 1–2, to facilitate their comparison with the equivalent coefficients for post-college education (Panel B) and scientists and engineers (Panel C). The coefficients for immigrant post–college are 20.7 and 29.8 in columns 1 and 2, 1.6–2.0 times as high as for immigrant college graduates, compared to a ratio of 2.0 the NSCG data. The coefficients indicate positive spill–overs, as the effect of a one percentage point increase in the immigrant post–college share in the individual data was 12%. The coefficients for the share of native post–college educated are not statistically significant, though the point estimates are higher for the longer differences, yielding an immigrant/native ratio of 3.5 at 50–year differences compared to 3.1 in the NSCG. For scientists and engineers in panel C columns 1–2, a one percentage point increase raises patents by 52 log points. This is high compared with the direct NSCG effect of about 19% and compared with the effect of natives at 50–year differences (25 log points), given that in the NSCG the immigrant patenting advantage over natives was only 35% amongst scientists and engineers. We return to this discrepancy below.

In columns 3 and 4 we repeat the regressions of columns 1 and 2, using the unlogged dependent variable and reporting coefficients multiplied by 100. For immigrants, the 50–year difference yields smaller coefficients than the ten–year difference. For immigrant college graduates in Panel A, a one percentage point increase in their share is associated with a 0.000037 (column 3) or 0.000027 (column 4) increase in patents per capita, which represent respectively 16.1% and 11.7% increases compared to the mean, close to the estimates in columns 1 and 2. The coefficients for post–college immigrants (Panel B) are 1.9–2.0 times the magnitude of the college immigrant coefficients, as we would expect, but are statistically insignificant. The disparity between ten and 50–year differences is large for the regressions using scientists and engineers (Panel C). The 50–year coefficient is similar in magnitude to the results from the log specification: the coefficient of 1.35 (column 4) means that a one percentage point increase in the skilled immigrant share is associated with a 58.7% increase compared to the mean. The skilled immigrant coefficients in columns 3–4 are not very sensitive to the covariates included, while the results in columns 1–2 are much smaller if the 1940 covariates (including land area) are not included.

We have repeated all the least squares regressions of Table 6 splitting the skilled natives according to whether they lived in the state of their birth or not (these results are not reported). For long differences, it is the coefficient on the change in the share of skilled natives born in another state that is larger and statistically significantly positive. For short and medium differences, which coefficient is more larger depends on the skill group.

Before presenting instrumental variables results, we display in Figure 3 the correlation between the change in the immigrant college share and its instrument (the predicted change) for each decade, and plot the weighted regression line. If the instrument were picking up shocks to patenting from around 1940, we would expect the instrument to gradually weaken over time. Instead, the instrument is weak in the low immigration decades of 1940–1950 and 1950–1960, strong thereafter. The unreported figures for immigrant post–college and scientist and engineer shares indicate similar correlations, though they are less significant for scientists and engineers.

We now proceed to present the results of instrumental variables estimation and other specification checks, focusing on the log specification and ten–year differences, and reporting only the coefficient on the change in the skilled immigrant share. For conciseness we present the full results only for the case of college proxying for skill, in Table 7. Row 1 shows that in the base specification, instrumental variables increases the coefficient to 30, more than twice the least squares coefficient of 13. The instrument is strong in the first stage, as indicated by the value in brackets of 27 for the F–statistic for the excluded instrument's significance in the first stage (the first stage itself, along with all other first stages for the table, is shown in Appendix Table 3). The higher magnitude of the instrumental variables estimate may indicate that in least squares, measurement error's bias towards zero is more important than upward bias due to the endogenous location choice of immigrants, a possibility mooted by Card and DiNardo (2000) in a similar context. It seems less likely that skilled immigrants whose behavior is affected by the instrument (skilled immigrants whose location decision is affected by historical geographic or taste considerations) are more inventive than other immigrants.

In rows 2 and 3 we check the robustness of the results to different samples. Without California (row 2), the least squares estimate falls from 13.2 to 9.2 and the instrumental variables estimate from 30 to 26. Without differences involving the year 2000, the point estimates fall more. In row 4 we return to the full sample and add seven dummies for BEA regions, which pick up region–specific trends in per capita patenting. This decreases the point estimates compared to row 1. The region coefficients are jointly significant, as are the coefficients for all sets of covariates we add in this table. In row 5, we use state instead of region dummies, which mainly serves to increase the standard errors. In row 6, we revert to using BEA region dummies, and add controls for the share of workers in electrical engineering in 1980 interacted with year dummies, which decreases the least squares estimate from 11.5 in row 4 to 9.6, but leaves the instrumental variables estimate little changed at 23.

Until this point, the regressions have not controlled for the state's 1940 shares of the eighteen immigrant groups that enter the calculation of the instruments (λ_{ik}). We add these shares to the controls in row 7, which increases the coefficients slightly as well as the standard errors, rendering the least squares estimate insignificant. As the point estimates change little, we do not include the 1940 shares in the remaining rows.

Since the change in the native skilled share is endogenous, the instrumental variable estimate of the effect of the change in the immigrant skilled share is only unbiased if the two variables are independent. Since this is obviously not the case (the correlation in the first stage is significantly negative), we experiment in row 8 with dropping the control for the change in the share of college natives. Compared to row 6, the least squares coefficient falls slightly, but the instrumental variables coefficient falls considerably, from 23.1 to 17.6.

In row 9 we propose a more parsimonious specification aimed at capturing post–1980 patenting changes, adding to the base specification only BEA region dummies interacted with a dummy for post–1980 (i.e. for differences including 1990 or 2000). These results are very close to those of row 8, although the addition of these covariates has weakened the instrument considerably in the first stage, as evidenced by the fall in the F–statistic in brackets. In row 10 we drop the change in the native college share from the covariates of the row 9 specification, and the estimates fall to the lowest values in the table: 7.0 for least squares and 12.3 for instrumental variables.

Our preferred specifications for least squares are rows 6 and 9 (which include the native skilled share), while for instrumental variables they are the counterparts excluding the native skilled share in rows 8 and 10. We present their results in Table 8 for all three skill groups (repeating the college results). For immigrant college graduates (columns 1 and 2), a one percentage point increase in share increases patenting per capita by 8–10% in least squares and 12–18% in instrumental variables, more than the 6% based on the individual–level data (statistically significantly so in the case of the highest coefficient), and therefore implying positive spill–overs. For post–college immigrants (columns 3 and 4), the upper specifications lead to insignificant coefficients similar in size to the college coefficients: 11.3 and 18.9 for least squares and instrumental variables respectively. It seems implausible that the effects would not be larger than for college immigrants (and this specification is unusual in this regard), so we put more weight on the lower specifications which yields coefficients of 15.9 and 27.0, about double the college coefficients, as would be expected from the individual–level analysis. The individual–level effect calculated for the immigrant post–college share was 12%, so overall the coefficients imply considerable positive spill–overs.

We do not present instrumental variables results for immigrant scientists and engineers, as the instrument is too weak in the first stage, but the least squares coefficients in column 5 are 38.2 and 30.7 (significant only at the 10% level), compared to a 19% effect calculated with the individual–level data. The scientist and engineer coefficients are 3.7–4.0 times their college counterparts in column 1, which still seems slightly high compared to the ratio of 3.1 in the individual–level data. For immigrant scientist and engineers in the specifications of this table, contrary to the cases of immigrant college and post–college, the coefficient on the share generally falls as the difference length increases. This means that at longer differences, the immigrant and native shares of scientists and engineers have similar coefficients, as would be expected based on the individual–level results. For example, in the 50–year counterpart to the upper specification of Table 8, the coefficient on the immigrant scientist and engineer share is 27.0 (standard error 16.2) while the native coefficient is 22.9 (standard error 5.8). These values imply ratios of immigrant to native and of immigrant scientists/engineers to immigrant college very similar to in the NSCG. The instrument is also more powerful at this long difference (an F–statistic of 11 in the first stage), and the instrumental variables coefficient is 61.4 (standard error 28.7). These are our preferred coefficients for scientists and engineers.

In Table 9 we investigate further using the Harvard Business School patent data for 1971–2001. In row 1 we repeat the least squares base specification for log patents per capita for this smaller sample, and obtain slightly smaller point estimates for immigrant college (10.7), post–college (15.2) and scientists and engineers (45.7) compared to those in Table 6. In row 2 we change the dependent variable to be the log of patent citations per capita, and in row 3 we add region dummies to this specification. The results are not very different from the results for patent counts, suggesting immigrants are not generating patents of lower quality than native patents. Unreported instrumental variables coefficients are larger (21 for college graduates in the base specification) but insignificant.

In rows 4–9 we present the results for the six categories of patent. The standard errors are high when the data are split in this way, and we elect simply to present the least squares base specification rather than various specifications with insignificant coefficients. From the reported results as well as the unreported results, the only firm conclusions are that there is no effect for mechanical patents, and a negative effect for "other" patents. The beneficial effects of immigration are therefore spread across computer and communications patents, electrical and electronic patents, drug and medical patents, and chemical patents.

4 Conclusions

In this paper we have combined individual and aggregate data to demonstrate the important boost to innovation provided by skilled immigration to the United States in 1940–2000. A calculation for 1990–2000, when patenting per capita rose 63%, puts the magnitudes of the effects in context. The 1.3 percentage point increase in the share of the population composed of immigrant college graduates and the 0.7 percentage point increase in the share of post–college immigrants both increased patenting per capita by about 12% based on least squares[19] and 21% based on instrumental variables. The 0.45 percentage point increase in immigrant scientists and engineers increased patenting per capita by about 13% based on least squares[20] and 32% based on instrumental variables. These impacts include the positive spill–overs of skilled immigrants, which are a substantial share of the total impact: calculations based on individual–level data of the impacts without spill–overs suggest impacts of about 8–9% for all three skill groups.[21]

We find that a college graduate immigrant contributes at least twice as much to patenting as his or her native counterpart. The difference is fully explained by the greater

[19] College: Table 8 column 1 average coefficient 9.0, $9.0 \times 1.3 = 11.7$ log points= 12%; Post–college: Table 8 column 3 coefficient 15.9, $15.9 \times 0.7 = 11.1$ log points = 12%.

[20] Coefficient 27.0 from text, $27.0 \times 0.45 = 12.1$ log points= 13%.

[21] $6.1\% \times 1.3 = 7.9\%; 12.2\% \times 0.7 = 8.5\%; 18.9\% \times 0.45 = 8.5\%$

share of immigrants with science and engineering education, implying immigrants are not innately more able than natives. Indeed, immigrants are less likely to have patented recently than observably similar native scientists and engineers. Despite this, the fact that immigrants increase patenting per capita shows that their presence in the United States provides a previously uncharacterized benefit to natives, assuming the immigrants would have been less innovative or less able to commercialize their innovation elsewhere or that U.S. natives benefit more from innovation and commercialization in the United States than abroad. We can make a crude calculation of the benefit using the results of Furman, Porter and Stern (2002), who find that the elasticity of a country's GDP with respect to its patent stock is 0.113, controlling for capital and labor. This elasticity implies that the influx of immigrant college graduates in the 1990s increased U.S. GDP per capita by 1.4–2.4%.

One should be cautious in drawing the conclusion that innovation could be sustained by simultaneously subsidizing natives to study science and engineering and cutting immigration of scientists and engineers. The additional natives drawn into science and engineering might have lower inventive ability than the excluded immigrants, and such natives might have contributed more to the U.S. economy outside science and engineering. While evidence in the paper of positive spill–overs from scientists and engineers appears to support the dual policies of subsidizing native science and engineering study and increasing immigration of scientists and engineers, it is possible that members of other skilled professions provide equally large spill–overs that are simply more difficult to measure. Finally, the paper leaves for future research the question of which immigration pathways lead to the most successful immigrants: for example, admitting science and engineering graduate students and facilitating their remaining in the United States after graduation compared with admitting more scientists and engineers on temporary work visas.

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Appendix A: Theory

A.1 Model

The occupations of skilled immigrants to the United States depend in part upon the choices of potential immigrants, even if other factors are also at work. U.S. employers and universities, for example, influence the allocation of visas. Also, scientists and engineers might be common among immigrants because market conditions in the sending countries lead a larger share of foreigners than Americans to study science and engineering. Nevertheless, it is likely that self–selection is in part responsible for the fact that skilled immigrants of all visa types are more likely than skilled natives to have studied science and engineering (as shown by the National Survey of College Graduates).

We consider a world with two countries, the origin o and the potential destination d, and three types of labor L_k: scientific labor L_s, professional labor L_p and unskilled labor L_u. We assume that wages for each type of labor are higher in country d, so that immigration goes in one direction only: $w_k^d > w_k^o$ for all k. The migration cost is M^d with a distribution $g(M^d)$ on $[M_L^d, M_H^d]$. The cost may vary for an individual for many reasons such as relatives in the destination country, number of children, language skills, adaptation capacity, etc.

Consider the decision of an origin worker to emigrate. If she chooses to stay in the origin country, a worker of skill category k will receive a real net wage w_k^o with certainty. Workers of all three skill categories can find an unskilled job with certainty if they move to country d, but professional migrants can only find a professional job in country d with probability P_{pp}^d, and scientific migrants can only find a scientific job with probability P_{ss}^d (and scientific workers cannot work as professionals and vice–versa). Moreover, while scientific knowledge is equivalent in the two countries, a professional migrant needs to adapt her skills at cost $C_p^d > 0$ in order to get a professional job in country d. Thus, $P_{pp}^d = 0$ unless the worker adapts her skills.

We assume workers are risk neutral, have perfect access to credit, care only about consumption, and therefore maximize the expected present value of lifetime income. The expected wage of an worker in the origin country is

$$E[w|k] = P(\text{emigrate to } d)[E(w^d|k) - M^d|\text{emigrate to d}] + (1 - P(\text{emigrate to } d))w_k^o, \quad (4)$$

where $P(\text{emigrate to } d)$ is the probability of migration. Assuming that the worker prefers the status quo in case of indifference, she will migrate if

$$E(w^d|k) - M^d > w_k^o \iff \Gamma_k^d \equiv E(w^d|k) - w_k^o > M^d. \quad (5)$$

Thus, the worker will emigrate to country d with probability $G(\Gamma_k^d)$. The expected gain from emigration to country d for unskilled workers is

$$\Gamma_u^d = w_u^d - w_u^o, \quad (6)$$

for professional workers is

$$\begin{aligned}
\Gamma_p^d &= \overbrace{\max\{w_u^d, P_{pp}^d w_p^d + (1-P_{pp}^d)w_u^d - C_p^d\}}^{E[w^d|k=p]} - w_p^o \\
&= w_u^d + \max\{0, P_{pp}^d(w_p^d - w_u^d) - C_p^d\} - w_p^o \\
&= w_u^d - w_u^o + \max\{0, P_{pp}^d(w_p^d - w_u^d) - C_p^d\} - w_p^o + w_u^o \\
&= \Gamma_u^d + \underbrace{max\{0, \underbrace{P_{pp}^d(w_p^d - w_u^d)}_{\text{Expected productive skill premium in country } d} - C_p^d\}}_{\text{Net expected productive skill premium in country } d} - \underbrace{(w_p^o - w_u^o)}_{\text{Productive skill premium at home}},
\end{aligned} \tag{7}$$

and for scientific workers is

$$\begin{aligned}
\Gamma_s^d &= \overbrace{P_{ss}^d w_s^d + (1-P_{ss}^d)w_u^d}^{E[w^d|k=s]} - w_s^o \\
&= w_u^d + P_{ss}^d(w_s^d - w_u^d) - w_s^o \\
&= w_u^d - w_u^o + P_{ss}^d(w_s^d - w_u^d) - w_s^o + w_u^o \\
&= \Gamma_u^d + \underbrace{P_{ss}^d(w_s^d - w_u^d)}_{\text{Net expected innovative skill premium in country } d} - \underbrace{(w_s^o - w_u^o)}_{\text{Innovative skill premium at home}}.
\end{aligned} \tag{8}$$

We assume that the cost of acquiring professional and scientific skills is the same, and that the expected benefits must therefore be the same. If this were not the case, workers in the origin country would all choose the more profitable skill category. This would decrease the marginal value of labor of this category, and thus its wage, until equality was attained again. Therefore, we have

$$G(\Gamma_s^d)E(\Gamma_s^d - M^d|M^d < \Gamma_s^d) + w_s^o = G(\Gamma_p^d)E(\Gamma_p^d - M^d|M^d < \Gamma_p^d) + w_p^o, \tag{9}$$

which can be rearranged as

$$G(\Gamma_s^d)E(\Gamma_s^d - M^d|M^d < \Gamma_s^d) - G(\Gamma_p^d)E(\Gamma_p^d - M^d|M^d < \Gamma_p^d) = w_p^o - w_s^o. \tag{10}$$

Let $\varphi(\Gamma_k^d) \equiv G(\Gamma_k^d)E(\Gamma_k^d - M^d|M^d < \Gamma_k^d)$. Noting[22] that $\frac{\partial\varphi(\Gamma_k^d)}{\partial\Gamma_k^d} \geqslant 0$ (strict inequality if $\Gamma_k^d > I_L^d$), we have that $\Gamma_s^d - \Gamma_p^d$ is of opposite sign from $w_s^o - w_p^o$. We can use this to show that, under some conditions, we must have $\Gamma_s^d > \Gamma_p^d$ i.e. a greater return to migration for scientific than professional workers.

Proposition 1. *If $w_u^d < w_s^o$, then a necessary condition that $\Gamma_s^d > \Gamma_p^d$ is*

$$P_{pp}(w_p^d - w_u^d) - C_p^d < \frac{1}{G(\Gamma_p^d)}[(w_s^o - w_p^o)[1 - G(\Gamma_p^d)] + \phi(\Gamma_p^d) - \phi(\Gamma_s^d) + G(\Gamma_s^d)P_{ss}(w_s^d - w_u^d)],$$

and a sufficient condition is

$$C_p^d > P_{pp}(w_p^d - w_u^d).$$

[22] For the proof, see below.

Proof. See below. □

Focusing on the simpler sufficient condition, we see that for an origin country whose scientific workers earn more at home than unskilled workers in the destination, scientific workers have a larger expected gain from migration than professional workers if the skill adaptation costs for professional migrants are larger than the expected professional skill premium in the destination. Therefore, scientific workers are more likely to migrate than professional workers. No correspondingly simple condition exists for the case of $w_u^d > w_s^o$, where unskilled workers in the destination earn more than scientific workers in the origin country.[23]

A.2 Proof of Proposition 1

Proposition 1. *If $w_u^d < w_s^o$, then a necessary condition that $\Gamma_s^d > \Gamma_p^d$ is*

$$P_{pp}(w_p^d - w_u^d) - C_p^d < \frac{1}{G(\Gamma_p^d)}[(w_s^o - w_p^o)[1 - G(\Gamma_p^d)] + \phi(\Gamma_p^d) - \phi(\Gamma_s^d) + G(\Gamma_s^d)P_{ss}(w_s^d - w_u^d)],$$

and a sufficient condition is

$$C_p^d > P_{pp}(w_p^d - w_u^d).$$

Proof. This is a proof by contradiction. First, replace (7) and (8) in (9). This gives

$$\begin{aligned} G(\Gamma_s^d)[\Gamma_u^d + P_{ss}(w_s^d - w_u^d) - (w_s^o - w_u^o) - E(M^d|M^d < \Gamma_s^d)] + w_s^o = \\ G(\Gamma_p^d)[\Gamma_u^d + \max\{0, P_{pp}(w_p^d - w_u^d) - C_p^d\} - (w_p^o - w_u^o) - E(M^d|M^d < \Gamma_p^d)] + w_p^o. \end{aligned}$$

Using (6) and rearranging, we get

$$\begin{aligned} G(\Gamma_s^d)[w_u^d + P_{ss}(w_s^d - w_u^d] + [1 - G(\Gamma_s^d)]w_s^o - \phi(\Gamma_s^d) = \\ G(\Gamma_p^d)[w_u^d + \max\{0, P_{pp}(w_p^d - w_u^d) - C_p^d\}] + [1 - G(\Gamma_p^d)]w_p^o - \phi(\Gamma_p^d), \end{aligned}$$

where

$$\phi(\Gamma_k^d) \equiv G(\Gamma_k^d)E(M^d|M^d < \Gamma_k^d).$$

Also, using the Fundamental Theorem of Calculus, we have that $\frac{\partial\phi(\Gamma_k^d)}{\partial\Gamma_k^d} > 0$.

Adding and subtracting $G(\Gamma_p^d)w_s^o$ on the right side and rearranging gives

$$\begin{aligned} (w_u^d - w_s^o)[G(\Gamma_s^d) - G(\Gamma_p^d)] = (w_p^o - w_s^o)[1 - G(\Gamma_p^d)] + \phi(\Gamma_s^d) - \phi(\Gamma_p^d) \\ + G(\Gamma_p^d)\max\{0, P_{pp}(w_p^d - w_u^d) - C_p^d\} - G(\Gamma_s^d)P_{ss}(w_s^d - w_u^d). \end{aligned}$$

[23] In principle, we can maximize discounted lifetime income of workers in the origin country, taking the migration option into account and assuming a distribution of the cost of skilled education relative to unskilled education, and calculate the share of workers at each skill level, for migrants and non–migrants. In practice, the resulting non–linear equations cannot be solved analytically.

Now, suppose that $w_u^d < w_s^o$ and $\Gamma_p^d > \Gamma_s^d$. We have that the left side of the equation is positive, since $G(.)$ is a density function, so it is increasing. Now, let us look at the right side of the equation. We have:

$$\underbrace{\underbrace{(w_p^o - w_s^o)}_{\leqslant 0,\text{ since }\Gamma_p^d > \Gamma_s^d} \underbrace{[1 - G(\Gamma_p^d)]}_{\geqslant 0,\text{ since }G(.)\text{ is a density}}}_{\leqslant 0} + \underbrace{\phi(\Gamma_s^d) - \phi(\Gamma_p^d)}_{\leqslant 0,\text{ since }\Gamma_p^d > \Gamma_s^d}$$

$$+ G(\Gamma_p^d)\max\{0, P_{pp}(w_p^d - w_u^d) - C_p^d\} \underbrace{-G(\Gamma_s^d)P_{ss}(w_s^d - w_u^d)}_{<0,\text{ else, no one wants skilled job}}.$$

Therefore, the right side is negative if

$$\max\{0, P_{pp}(w_p^d - w_u^d) - C_p^d\} < \frac{1}{G(\Gamma_p^d)} \underbrace{[(w_s^o - w_p^o)[1 - G(\Gamma_p^d)] + \phi(\Gamma_p^d) - \phi(\Gamma_s^d) + G(\Gamma_s^d)P_{ss}(w_s^d - w_u^d)]}_{>0}.$$

Thus, a necessary condition to have the right side negative is

$$P_{pp}(w_p^d - w_u^d) - C_p^d < \frac{1}{G(\Gamma_p^d)}[(w_s^o - w_p^o)[1 - G(\Gamma_p^d)] + \phi(\Gamma_p^d) - \phi(\Gamma_s^d) + G(\Gamma_s^d)P_{ss}(w_s^d - w_u^d)],$$

and a sufficient condition is

$$C_p^d > P_{pp}(w_p^d - w_u^d).$$

Under these conditions, we get a contradiction, since the left side is strictly positive, but the right side is negative. As long as either of these conditions holds, we must have $\Gamma_p^d < \Gamma_s^d$ if $w_u^d < w_s^o$.

□

A.3 Proof that $\partial\varphi(\Gamma_k^d)/\partial\Gamma_k^d \geq 0$

Proof. We will show that $\partial\varphi(\Gamma_k^d)/\partial\Gamma_k^d \geq 0$ with strict inequality if $\Gamma_k^d > M_L^d$, where M_L^d is the lower bound on immigration cost. First, note that

$$\varphi(\Gamma_k^d) = G(\Gamma_k^d)E(\Gamma_k^d - M^d | M^d < \Gamma_k^d) = \int_{M_L^d}^{\Gamma_k^d} (\Gamma_k^d - M^d) g(M^d) dM^d$$

$$= \Gamma_k^d \underbrace{\int_{M_L^d}^{\Gamma_k^d} g(M^d)dM^d}_{G(\Gamma_k^d)} - \underbrace{\int_{M_L^d}^{\Gamma_k^d} M^d g(M^d)dM^d}_{\phi}$$

$$\partial\varphi(\Gamma_k^d)/\partial\Gamma_k = G(\Gamma_k^d) + \Gamma_k g(\Gamma_k^d) - \underbrace{\partial\phi/\partial\Gamma_k^d}_{=\Gamma_k g(\Gamma_k^d)\text{ using Fundamental Theorem of Calculus}}$$

$$= G(\Gamma_k^d) \geq 0, \text{ since G(.) is a density function}$$

□

Appendix B: Algebra for Equation (1)

If immigrants' share of the population grows by one percentage point,

$$\frac{M^S + \Delta M^S}{POP + \Delta M^S} - \frac{M^S}{POP} = 0.01,$$

which implies after some rearranging that

$$\Delta M^S = \frac{0.01 POP}{0.99 POP - M^S}.$$

Therefore, the percent increase in the population can be calculated as

$$\frac{\Delta M^S}{M^S} = \frac{POP}{M^S} \frac{0.01}{0.99 - \frac{M^S}{POP}} = \frac{1}{\alpha_1} \frac{0.01}{0.99 - \alpha_1}.$$

The percent increase in the population is

$$\frac{\Delta M^S}{POP} = \frac{0.01}{0.99 - \frac{M^S}{POP}} = \frac{0.01}{0.99 - \alpha_1}. \tag{11}$$

We calculate the percent increase in patents assuming that the additional immigrants continue to patent at rate $\frac{P^{MS}}{M^S}$:

$$\frac{\Delta P^{MS}}{P} = \frac{1}{P} \frac{P^{MS}}{M^S} \Delta M^S = \alpha_0 \frac{\Delta M^S}{M^S}. \tag{12}$$

The expressions (11) and (12) can then be substituted into the expression for the percent increase in patents per capita on the left hand side of equation (1) to obtain the expression on the right hand side.

Appendix C: Data

C.1 National Survey of College Graduates

The data were collected between October 2003 and August 2004 by the U.S. Bureau of the Census, on behalf of the National Science Foundation. The data consist of a stratified random sample of people reporting having a bachelor's degree or higher on the long form of the (April) 2000 census, who were under age 76 and living in the United States or its territories including Puerto Rico in the reference week of October 1, 2003. We drop respondents living outside the United States and define as immigrants those born outside the United States. Missing information is imputed with a hot deck procedure, and imputed values are not flagged. More information on the data is provided at www.nsf.gov/statistics/showsrvy.cfm?srvy_CatID=3&srvy_Seri=7#fn1. The data are available at www.nsf.gov/statistics/sestat/.

C.2 Patents

We combine two patent series from the U.S. Patent and Trademark Office. The first series was compiled for me by the USPTO based on their electronic records which begin in 1963. This series is utility patents by state and year of application. Year of application is preferred to year of grant as it is a more accurate match to the time of invention. The second series (U.S. Department of Commerce 1977) is from paper–based USPTO records of patents by state and grant year 1883–1976 (application year is not available pre–1963). Grants lag applications by a median of three years between 1950 and 1963 (according to our US–wide calculations based on Lexis–Nexis), so we lead this series three years. Patents grants are also more volatile than patent applications (Hall 2005), so we smooth the series with a three year moving average. Finally, because for 1930–1960 plants and designs cannot be separated from utility patents, we leave them in for the whole series, calculate by state the average percent gap in the overlap years of the two series (18% on average), and reduce the old series by this percent. We then merge the series, using the adjusted paper series values only for pre–1963. The USPTO attributes a patent to a state according to the home address of the first–listed inventor.

We have also used an extract from the Harvard Business School patent data file, which contains information on utility patents granted from 1975 to 2007, arranged by year of application and patent class. We have aggregated the patent classes to six categories using the classification in Hall, Jaffe and Trajtenberg (2001) and our own classification of patent classes created since 1999. In particular, we attribute classes 506 and 977 to chemical patents; classes 398, 701–720, 725 and 726 to computers and communication patents; and classes 901 and 903 to mechanical patents. We have not been able to find definitions for some patent classes created in 2006 or later (which affects some patents applied for in earlier years), and a small number of patents have a missing patent class. For the application years we used, 0.04% of patents are not allocated to one of our six categories. To examine patents by category, we have simply attributed 1974 values (most patents granted in 1975 were applied for in 1974 or earlier) to 1971, then used 1971, 1981, 1991 and 2001 patent values, and 1970, 1980, 1990 and 2000 values for the dependent variables. Some small states do not have patents in every category in every year, and in the analysis of log patents these observations are missing.

The extract also contains the number of citations made to patents in each patent class, state and application year. These may be viewed as a proxy for the quality of the patent. We calculate citations per patent from 1974 onwards for each state. We then run a regression of this ratio on a trend for each state from 1974–1980, and use the resulting coefficient to predict the 1971 value of citations per patent for each state. We then return to our original, longer patent series obtained directly from the USPTO, and multiply the patents by the ratio for 1971 onwards. We can then study citations, or quality–adjusted patents, for 1971, 1981, 1991 and 2001.

C.3 Immigration, education, age, occupation, labor force status

We use extracts from the Integrated Public Use Microdata Series for the United States Census, available at usa.ipums.org/usa/, and aggregate to the state level using the weights provided. Variables computed as shares (other than the excluded instruments) are computed as shares of the population or workers aged 18–65, and average population age is the average age of people aged 18–65. Immigrants are people born outside the United States. We use the census–provided edurec variable to identify college graduates (16 years of education or more in the 1940–1980 censuses, and a college or higher degree in the 1990 and 2000 censuses) and high–school dropouts (11 or fewer years of education). People with post–college education are people with 17 or more years of education in the 1940–1980 censuses, and a post–college degree in 1990 and 2000. This is the highest level of education that can be distinguished for the whole 1940–2000 period. Alaska and Hawaii are not in the 1940 and 1950 IPUMS and we drop them from the analysis. The SIC codes we count as electrical engineering are 321, 322, 342, 350, 371, 372.

C.4 Other data

We use Bureau of Economic Analysis data for total state population (used to weight the regressions) and for state personal income per capita (available from 1929 onwards, unlike gross state product which is not available for our whole period). The data are available at www.bea.gov/regional/spi/.

Department of Defense procurement contracts by state are available on paper for the early years in *Prime Contract Awards by State, Fiscal Years 1951–1978*, published by the Department of Defense, OASD (Comptroller), Directorate for Information Operations and Control. The later years are available online at www.fpds.gov. Some measurement error in the attribution to states is involved, as recipient firms may subcontract the work to firms in other states. Also, in the electronic records for 1978–1983, 1986 and 1989 (of which only 1980 is relevant for the paper), the California numbers seem to be too small by a factor of 1000, so we have multiplied them by 1000. (We have obtained scanned versions of the paper documents for these years: the values for the non–problematic states and years are only approximately the same as those online, but the problematic California years are indeed about 1000 times higher than the online version.) We attribute the 1951 value to 1950, and set changes in the values involving 1940, for which data are not available, to zero.

We obtain the land area of each state from the US. Census Bureau at www.census.gov/population/censusdata/90den_stco.txt.

Table 1: Patenting by immigrant status

	(1)	(2)	(3)	(4)	(5)	(6)
	College graduates		Post-college graduates		Scientists and engineers	
	Immigrant	Native	Immigrant	Native	Immigrant	Native
Any patent granted	0.019	0.009	0.036	0.013	0.062	0.049
Number patents granted	0.057	0.028	0.112	0.036	0.178	0.132
Any patent commercialized	0.012	0.006	0.021	0.008	0.037	0.030
Number patents commercialized	0.029	0.017	0.054	0.019	0.084	0.074
Share immigrant	0.136		0.161		0.240	
Observations	20,294	71,186	11,729	30,410	6724	15,502

Notes: Shares weighted with survey weights. Patents questions only asked of respondents who had ever worked. Whether a patent has been granted refers to period from October 1998 to the survey in 2003, and whether a patent has been commercialized or licensed refers to those patents granted in the same period.

Source: 2003 National Survey of College Graduates.

Table 2: Means of aggregate variables

	(1) 1940-2000	(2) 1940	(3) 2000
Patents/population, x100	0.023	0.018	0.035
	(0.015)	(0.013)	(0.020)
Share of population 18-65 that is:			
Immigrant, college education and above	0.015	0.003	0.035
Native, college education and above	0.127	0.041	0.200
Immigrant, post-college education	0.007	0.001	0.016
Native, post-college education	0.050	0.011	0.077
Share of workers 18-65 that are:			
Immigrant, scientists and engineers	0.003	0.001	0.009
Native, scientists and engineers	0.022	0.006	0.035
Age of population 18-65	38.7	37.7	39.5
	(1.0)	(1.0)	(0.6)
DoD prime military procurement contracts	3236	1500	5528
(millions of nominal $)	(4386)	(1679)	(5809)
State personal income per capita (nominal $)	11976	594	29,851
	(11098)	(204)	(4094)
Land area (millions of square kilometers)	0.190	0.166	0.207
	(0.161)	(0.145)	(0.173)
Observations	343	49	49

Notes: Means of state-level variables for population 18-65, weighted by state population the year after the census. Standard deviations in parentheses. Patents and population are led by one year. Alaska and Hawaii are excluded. Patents are classified by year filed. The predicted increases in immigrant college share (instruments) are based on states' shares of 1940 immigrant high school graduates from various countries and national growth in college graduates from those countries (see text). The 1940 value of DoD procurement spending is not available, and the 1950 value is given instead of 1940, and the 1950-2000 average instead of 1940-2000.

Sources:
Education, age, occupation, nativity: U.S. Census Bureau, IPUMS decennial census microdata usa.ipums.org/usa/
Patents: U.S. Patent and Trademark Office, electronic and paper data.
State income, population: Bureau of Economic Analysis www.bea.gov/regional/spi/
Land Area: U.S. Census Bureau www.census.gov/population/censusdata/90den_stco.txt

Table 3: Patenting by field of study and field of study by immigrant status, college graduates

Field of highest degree	(1) Any patent granted	(2) Any patent commercialized	(3) Share immigrants	(4) Share natives
Computer science, math	0.017	0.012	0.079	0.036
Biological, agricultural and environment sciences	0.023	0.011	0.055	0.040
Physical sciences	0.066	0.039	0.036	0.017
Social and related sciences	0.004	0.002	0.093	0.108
Engineering	0.061	0.042	0.137	0.053
Other S&E (mainly health)	0.007	0.004	0.166	0.121
Non-S&E	0.004	0.003	0.434	0.624
All fields	0.011	0.007	1.00	1.00

Notes: Shares weighted by survey weights. "S&E" means science and engineering. Full sample (i.e. college graduates), 91,480 observations. Whether a patent has been granted refers to period from October 1998 to the survey in 2003, and whether a patent has been commercialized or licensed refers to those patents granted in the same period.

Source: 2003 National Survey of College Graduates.

Table 4: Effect of immigrant status on patenting

	(1)	(2)	(3)	(4)	(5)	(6)
		Any patent granted?			Any patent commercialized?	
College graduates	0.0100**	0.0009**	-0.0007*	-0.0005	0.0062**	-0.0004
	(0.0010)	(0.0005)	(0.0004)	(0.0003)	(0.0008)	(0.0003)
Pseudo-R^2	0.01	0.15	0.19	0.21	0.01	0.18
Post-college graduates	0.0226**	0.0014**	0.0004	0.0005	0.0135**	0.0002
	(0.0018)	(0.0008)	(0.0006)	(0.0006)	(0.0014)	(0.0004)
Pseudo-R^2	0.02	0.21	0.24	0.26	0.02	0.21
Scientists and engineers	0.0131**	0.0031	-0.0095**	-0.0074**	0.0063**	-0.0052**
	(0.0039)	(0.0031)	(0.0027)	(0.0026)	(0.0030)	(0.0020)
Pseudo-R^2	0.00	0.08	0.12	0.13	0.00	0.09
Major field of highest degree	--	Y	Y	Y	--	Y
Highest degree	--	--	Y	Y	--	Y
Age, age^2, sex, employed	--	--	--	Y	--	--

Notes: Marginal effect on dummy for foreign-born from weighted probits. There are 91,480 observations in the college graduate sample, 42,139 in the post-college sample and 22,226 in the scientist and engineer sample. All scientists and engineers are employed in the reference week. Post-college degrees include master's (including MBA), PhD and professional. There are 30 major field of study dummies (we combine the two S&E teacher training categories into one). Standard errors are in parentheses. ** indicates coefficients significant at the 5% level, * indicates coefficients significant at the 10% level.

Table 5: Effect of share of immigrant college graduates on log patents per capita

	(1)	(2)	(3)	(4)
Difference:	10 year	10 year	30 year	50 year
Δ Immigrant college	14.7**	13.2**	12.1**	14.9**
as share of population	(5.3)	(4.3)	(3.2)	(4.3)
Δ Native college	4.1**	1.9	4.8**	5.8**
as share of population	(1.9)	(2.3)	(1.8)	(2.1)
Δ Age (average)	0.064**	0.104**	0.163**	0.137**
	(0.028)	(0.035)	(0.041)	(0.066)
Δ DoD procurement (log)	-0.033	-0.039**	-0.081**	-0.063
	(0.025)	(0.017)	(0.035)	(0.041)
Land area (log)	0.046**	0.063**	0.169**	0.281**
	(0.007)	(0.013)	(0.032)	(0.055)
Population 1940 (log)	-0.056**	-0.062**	-0.161**	-0.252**
	(0.015)	(0.015)	(0.032)	(0.060)
State personal income per	-0.223**	-0.162**	-0.544**	-1.006**
capita 1940 (log)	(0.037)	(0.048)	(0.103)	(0.189)
Weighted	No	Yes	Yes	Yes
R^2	0.47	0.64	0.63	0.70
Observations	294	294	196	98

Notes: The dependent variable is the difference in log patents per capita across periods ranging from ten to 50 years, with a lead of one year compared to the independent variables. Weighted least squares regressions have weights $1/(1/pop_{t+1}+1/pop_{t-k+1})$, where k the length of the difference. Regressions also include year dummies. Standard errors clustered by state are in parentheses. ** indicates coefficients significant at the 5% level, * indicates coefficients significant at the 10% level.

Table 6: Effect of skilled immigrant shares on patents per capita

	(1)	(2)	(3)	(4)
	Δ Log patents per capita		Δ Patents per capita	
Difference:	10 year	50 year	10 year	50 year
Panel A. Skilled: college graduates as share of population				
Δ Skilled immigrant	13.2**	14.9**	0.368**	0.271*
	(4.3)	(4.3)	(0.173)	(0.158)
Δ Skilled native	1.9	5.8**	-0.010	0.134*
	(2.3)	(2.1)	(0.108)	(0.081)
R^2	0.64	0.70	0.49	0.42
Panel B. Skilled: post-college educated as share of population				
Δ Skilled immigrant	20.7*	29.8**	0.686	0.538
	(10.7)	(10.9)	(0.501)	(0.403)
Δ Skilled native	-1.3	8.4	-0.086	0.127
	(3.3)	(5.8)	(0.138)	(0.224)
R^2	0.63	0.66	0.48	0.38
Panel C. Skilled: scientists and engineers as share of workers				
Δ Skilled immigrant	52.4**	52.6**	2.318**	1.354**
	(20.7)	(16.1)	(0.990)	(0.661)
Δ Skilled native	9.4*	24.7**	0.212	0.665**
	(5.4)	(8.0)	(0.239)	(0.278)
R^2	0.67	0.74	0.56	0.52
Observations	294	98	294	98

Notes: The dependent variable is the difference in (log) patents per capita across periods ranging from ten to 50 years, with a lead of one year compared to the independent variables. Weighted least squares with weights $1/(1/pop_{t+1}+1/pop_{t-k+1})$, where k is equal to the difference length. All regressions include the covariates of Table 5. Standard errors clustered by state are in parentheses. Coefficients in columns 3-4 are multiplied by 100. ** indicates coefficients significant at the 5% level, * indicates coefficients significant at the 10% level.

Table 7: Effect of college immigrant shares on log patents per capita, ten-year differences, further specifications

	(1) WLS	(2) IV
1. Base specifications	13.2**	30.3**
	(4.3)	(7.2)
		[27]
2. Base specifications without California (288 observations)	9.2**	26.3**
	(4.3)	(7.1)
		[24]
3. Base specifications without year 2000 (245 observations)	8.8**	18.9**
	(3.5)	(7.1)
		[51]
4. Include BEA region dummies	11.5**	23.4**
	(4.5)	(5.4)
		[30]
5. Include state dummies	11.6**	24.5**
	(5.6)	(6.3)
		[31]
6. Include BEA region dummies	9.6**	23.1**
and % electrical workers 1980*year dummies	(4.7)	(7.0)
		[28]
7. Include BEA region dummies	10.1*	24.5**
and % electrical workers1980*year dummies	(5.8)	(7.8)
and 1940 immigrant shares (λ)		[39]
8. Include BEA region dummies	8.6*	17.6**
and % electrical workers1980*year dummies;	(4.3)	(5.6)
exclude share college natives		[27]
9. Include BEA region dummies*post-1980	8.4**	18.6**
	(3.4)	(7.6)
		[9]
10. Include BEA region dummies*post-1980;	7.0**	12.3**
exclude share college natives	(3.4)	(6.1)
		[10]

Notes: Each coefficient reported is the effect of a change in college immigrant share of the population from a different regression. The dependent variable is the difference in log patents across ten years, with a lead of one year compared to the independent variables. 294 observations unless otherwise noted. Weighted least squares (column 1) or instrumental variables (column 2) with weights $1/(1/pop_{t+1}+1/pop_t)$. The instruments are the predicted increase in college immigrant shares, based on states' shares of 1940 immigrants from various countries and subsequent national growth in college graduates from those countries (see text). F-statistic for test of joint significance of excluded instrument in the first stage in brackets. All regressions also include the covariates of Table 5 including the appropriate differenced share of skilled natives. Standard errors clustered by state are in parentheses. ** indicates coefficients significant at the 5% level, * indicates coefficients significant at the 10% level.

Table 8: Effect of skilled immigrant shares on log patents per capita, ten-year differences, preferred specifications

	(1)	(2)	(3)	(4)	(5)
Skill represented by:	College graduates		Post-college		Scientists/ engineers
	WLS	IV	WLS	IV	WLS
1. Include BEA region dummies, % electrical workers1980*year dummies; IV excludes share college natives	9.6**	17.6**	11.3	18.9	38.2*
	(4.7)	(5.6)	(8.3)	(14.3)	(20.3)
		[27]		[18]	
2. Include BEA region dummies*post-1980; IV excludes share college natives	8.4**	12.3**	15.9**	27.0**	30.7*
	(3.4)	(6.1)	(6.2)	(13.4)	(16.3)
		[10]		[11]	

Notes: Each coefficient reported is the effect of a change in skilled immigrant share from a different regression. The dependent variable is the difference in log patents across ten years, with a lead of one year compared to the independent variables. Weighted least squares (odd columns) or instrumental variables (even columns) with weights $1/(1/pop_{t+1}+1/pop_t)$. The instruments are the predicted increase in skilled immigrant shares, based on states' shares of 1940 immigrants from various countries and subsequent national growth in college graduates from those countries (see text). F-statistic for test of joint significance of excluded instrument in the first stage in brackets. All regressions also include the covariates of Table 5 including the appropriate differenced share of skilled natives. Standard errors clustered by state are in parentheses. 294 observations. ** indicates coefficients significant at the 5% level, * indicates coefficients significant at the 10% level.

Table 9: Effect of skilled immigrant shares on log patent citations per capita and log patents per capita by type, ten-year differences, 1970-2000

	(1)	(2)	(3)
Skill represented by:	College graduates	Post-college	Scientists/engineers
1. Patents	10.7**	15.2	45.7**
	(4.6)	(11.6)	(22.0)
2. Patent citations	9.9**	18.5	54.4**
	(4.8)	(12.4)	(24.2)
3. Patent citations, include	11.3**	24.2*	56.2*
BEA region dummies	(5.6)	(12.2)	(29.6)
4. Computer and communications	10.2	1.7	35.0
patents (137 observations)	(7.4)	(19.5)	(23.5)
5. Electrical and electronic patents	0.1	-2.2	6.9
(145 observations)	(6.1)	(15.4)	(23.9)
6. Drug and medical patents	12.5*	9.2	50.6
(146 observations)	(6.7)	(14.8)	(30.7)
7. Chemical patents	7.5	8.7	10.3
(145 observations)	(6.4)	(14.9)	(26.5)
8. Mechanical patents	-3.0	-15.7	3.8
	(3.9)	(9.0)	(16.1)
9. Other patents	-7.7**	-19.2**	-15.5
	(2.6)	(4.9)	(9.7)

Notes: Each coefficient reported is the effect of a ten-year change in skilled immigrant share from a different regression. The dependent variable is the difference in log patents per capita or log of patent citations per capita across ten years, with a lead of one year compared to the independent variables. Weighted least squares for 1970-2000 with weights $1/(1/pop_{t+1}+1/pop_t)$. All regressions include the covariates included in Table 5. Standard errors clustered by state are in parentheses. 147 observations, unless otherwise specified. ** indicates coefficients significant at the 5% level, * indicates coefficients significant at the 10% level.

Appendix Table 1: States' 1940 shares of national-level immigrants from various origins

Origin	(1) State's 1940 share of national total, all immigrants Mean	(2) Maximum	(3) State of maximum	(4) College grad immigrants National total 2000 - national total 1940
United Kingdom	0.050	0.19	New York	192,750
Ireland	0.059	0.32	New York	22,667
Italy	0.062	0.35	New York	45,368
Germany	0.052	0.23	New York	216,513
Poland	0.060	0.28	New York	66,284
Russia	0.064	0.37	New York	236,052
Other Europe	0.050	0.19	New York	348,471
Canada	0.038	0.21	Massachusetts	208,124
Mexico	0.043	0.39	California	263,006
Puerto Rico	0.096	0.90	New York	121,761
Cuba	0.047	0.41	Florida	125,089
Other Caribbean	0.073	0.61	New York	234,065
Central America	0.052	0.26	California	130,725
South America	0.069	0.47	New York	368,186
China	0.058	0.39	California	617,482
India	0.047	0.26	California	773,840
Other Asia	0.045	0.62	California	1,426,943
Rest of world	0.054	0.26	New York	549,302

Notes: State-level variables, means weighted by state population. Standard deviations in parentheses. 49 observations. Alaska and Hawaii are excluded. The minimum share is zero for all origins except for the United Kingdom, Germany, other Europe and Canada. Columns 1-3 are based on the full population, while column 4 is based on the population 18-65.

Appendix Table 2: Means of individual-level variables

	College graduates		Post-college		Scientists/engineers	
	Immigrant	Native	Immigrant	Native	Immigrant	Native
Highest degree:						
Bachelor's	0.58	0.65	--	--	0.44	0.68
Master's	0.28	0.26	0.66	0.74	0.39	0.26
Doctorate	0.07	0.03	0.17	0.08	0.16	0.06
Professional	0.07	0.06	0.17	0.17	0.01	0.01
Field of highest degree						
Computer science, mathematics	0.076	0.036	0.091	0.027	0.219	0.168
Biological, agricultural, environment science	0.056	0.040	0.061	0.030	0.092	0.093
Physical science	0.035	0.017	0.044	0.017	0.077	0.072
Social science	0.091	0.108	0.069	0.078	0.026	0.046
Engineering	0.132	0.053	0.131	0.037	0.397	0.321
Other S&E	0.164	0.121	0.199	0.157	0.069	0.058
Non-S&E	0.446	0.624	0.406	0.653	0.120	0.243
Sex (female)	0.48	0.50	0.43	0.49	0.24	0.23
Age	43.4	44.7	43.8	46.6	40.4	42.4
	(9.9)	(10.3)	(9.9)	(10.3)	(9.0)	(9.5)
Employed	0.86	0.85	0.89	0.87	1.00	1.00
Observations	21,248	71,304	12,042	30,460	6840	15,519

Notes: Means weighted with survey weights. S&E means science and engineering. "Other S&E" includes the social sciences. Native movers are natives living in a different census region from their census region of birth.

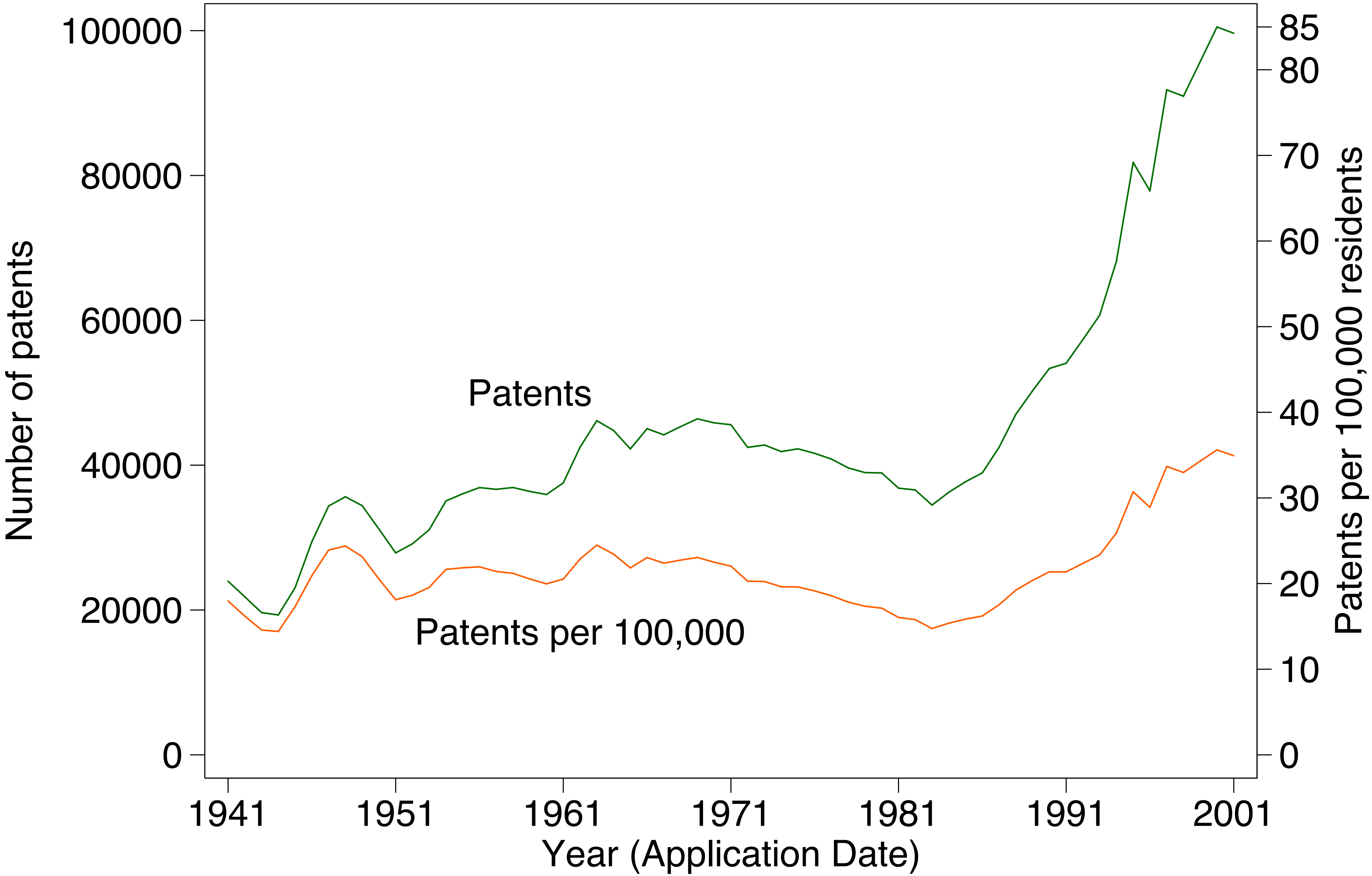
Source: National Survey of College Graduates

Appendix Table 3: First stage of instrumental variables regressions for ten-year differences

Skill represented by:	(1) College graduates	(2) Post-college
1. Base specifications	0.31**	0.29**
	(0.06)	(0.06)
R^2 [R^2 without excluded instrument]	0.78 [0.69]	0.75 [0.67]
2. Sample without California	0.25**	0.24**
(288 observations)	(0.05)	(0.06)
R^2 [R^2 without excluded instrument]	0.70 [0.63]	0.69 [0.63]
3. Sample without year 2000	0.45**	0.40**
(245 observations)	(0.06)	(0.06)
R^2 [R^2 without excluded instrument]	0.79 [0.59]	0.69 [0.55]
4. Include BEA region dummies	0.29**	0.27**
	(0.05)	(0.06)
R^2 [R^2 without excluded instrument]	0.83 [0.76]	0.80 [0.74]
5. Include state dummies	0.34**	0.33**
	(0.06)	(0.07)
R^2 [R^2 without excluded instrument]	0.89 [0.82]	0.86 [0.79]
6. Include BEA region dummies and % electrical workers 1980*year dummies	0.25**	0.25**
	(0.05)	(0.06)
R^2 [R^2 without excluded instrument]	0.83 [0.79]	0.80 [0.76]
7. Include BEA region dummies and % electrical workers 1980*year dummies and 1940 immigrant shares	0.29**	0.30**
	(0.05)	(0.06)
R^2 [R^2 without excluded instrument]	0.89 [0.85]	0.85 [0.81]
8. Include BEA region dummies and % electrical workers 1980*year dummies; exclude native skilled share	0.27**	0.29**
	(0.05)	(0.06)
R^2 [R^2 without excluded instrument]	0.83 [0.78]	0.84 [0.80]
9. Include BEA region dummies*post-1980	0.25**	0.26**
	(0.09)	(0.08)
R^2 [R^2 without excluded instrument]	0.81 [0.77]	0.78 [0.73]
10. Include BEA region dummies*post-1980; exclude native skilled share	0.27**	0.26**
	(0.09)	(0.08)
R^2 [R^2 without excluded instrument]	0.81 [0.76]	0.77 [0.73]

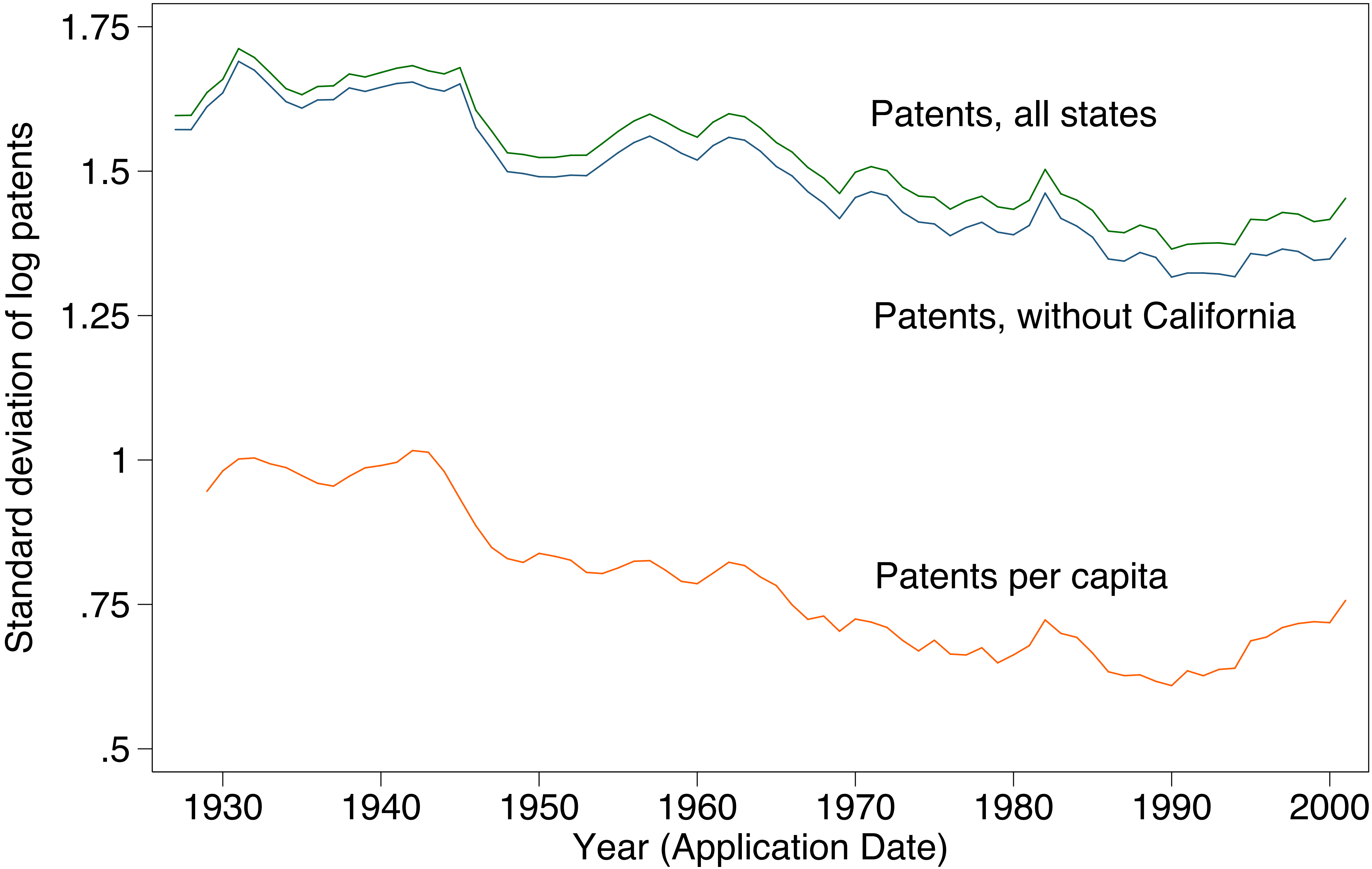
Notes: The dependent variable is the ten-year difference in the share of the population that is a skilled immigrant, with skill proxied by college in column 1, post-college in column 2. The coefficient reported is that on the excluded instrument, which is the predicted increase in immigrant college shares, based on states' shares of 1940 immigrant graduates from various countries and subsequent national growth in college graduates from those countries (see text). Weighted least squares with weights $1/(1/pop_{t+1}+1/pop_t)$. All regressions also include the covariates of Table 5 (except the difference in the skilled immigrant share). Standard errors clustered by state are in parentheses. 294 observations unless otherwise specified. ** indicates coefficients significant at the 5% level, * indicates coefficients significant at the 10% level.

Figure 1: U.S. Origin U.S. Patents 1941–2001



Source: USPTO, BEA and authors' calculations

Figure 2: Convergence in Patenting Across States 1929–2001



Source: USPTO, BEA and author's calculations

Fig 3: Actual, Predicted Change in Immigrant College Share