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 1950–2000 state panel, we show that natives are not crowded out by immigrants, and that immigrants do have positive spill–overs, resulting in an increase in patents per capita of about 15% 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 initial share of immigrant high school dropouts from Europe, China and India. In both data sets, the positive impacts of immigrant post–college graduates and scientists and engineers are larger than for immigrant college graduates.

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. 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.

The share of skilled immigrants that are scientists and engineers will clearly be an important determinant of the impact of skilled immigration on patenting. We therefore begin by examining theoretically the conditions under which foreigners with science and engineering education are more likely to move to the United States than other skilled foreigners. We then use the 2003 National Survey of College Graduates (NSCG) to examine whether immigrants patent more than natives because they have higher ability or merely more science and engineering education, and 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.

In order to account for immigrants' possible influence on natives or other immigrants, we turn to a panel of U.S. states from 1950–2000, based on data from the U.S. Patent and Trademark Office, the decennial censuses and other sources. We test whether skilled immigrants crowd out skilled natives from the states (and occupations) to which they move, and we provide estimates of skilled immigrants' impact on patents per capita that encompass both immigrants' own patenting and any positive 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 initial share of immigrant high school dropouts from Europe, China and India, the origin regions of at least 40% of skilled immigrants throughout the period.

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.[1]

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

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

variables, defining skilled immigration consistently across time and more broadly, and testing for crowd–out of natives. 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), who find that immigrant students increase U.S. university patenting and science and engineering publishing. 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 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.[2] The most closely related paper (other than those by Peri and Niebuhr) 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).[3]

[2]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.

[3]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

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. 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%.

This could overestimate the contribution of immigrants, if immigrants crowd out natives, but using the panel of states we show this does not happen. This is consistent with Borjas (2006), who finds that immigrants do not crowd out natives as a whole from graduate school. Instead, the state panel data show evidence of positive spill–overs of natives, since the estimates of the immigrant 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 about 15%. 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 about 20%. Consistent with the individual–level analysis, we find that immigrants have more than double the impact on innovation that natives do. 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 Theory

The share of skilled immigrants with science and engineering education will clearly be an important determinant of the impact of skilled immigration on patenting. It is likely that scientists and engineers are over–represented among migrants, since scientific and engi-

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.

neering 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. Chiswick and Taengnoi (2007) show immigrants work in less language–intensive occupations than natives. In this section, we show under what conditions foreign scientists and engineers are more likely to choose to migrate to the United States than other skilled foreigners.

Immigration to the United States does not depend only upon the choices of potential immigrants, of course. 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 NSCG).

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,

$P^d_{pp} = 0$ 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

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

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

$$E(w^d|k) - M^d > w^o_k \iff \Gamma^d_k \equiv E(w^d|k) - w^o_k > M^d. \quad (2)$$

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

$$\Gamma^d_u = w^d_u - w^o_u, \quad (3)$$

for professional workers is

$$\begin{aligned}
\Gamma^d_p &= \overbrace{\max\{w^d_u, P^d_{pp}w^d_p + (1 - P^d_{pp})w^d_u - C^d_p\}}^{E[w^d|k=p]} - w^o_p \\
&= w^d_u + \max\{0, P^d_{pp}(w^d_p - w^d_u) - C^d_p\} - w^o_p \\
&= w^d_u - w^o_u + \max\{0, P^d_{pp}(w^d_p - w^d_u) - C^d_p\} - w^o_p + w^o_u \\
&= \Gamma^d_u + \underbrace{max\{0, \underbrace{P^d_{pp}(w^d_p - w^d_u)}_{\text{Expected productive skill premium in country } d} - C^d_p\}}_{\text{Net expected productive skill premium in country } d} - \underbrace{(w^o_p - w^o_u)}_{\text{Productive skill premium at home}},
\end{aligned} \quad (4)$$

and for scientific workers is

$$\begin{aligned}
\Gamma^d_s &= \overbrace{P^d_{ss}w^d_s + (1 - P^d_{ss})w^d_u}^{E[w^d|k=s]} - w^o_s \\
&= w^d_u + P^d_{ss}(w^d_s - w^d_u) - w^o_s \\
&= w^d_u - w^o_u + P^d_{ss}(w^d_s - w^d_u) - w^o_s + w^o_u \\
&= \Gamma^d_u + \underbrace{P^d_{ss}(w^d_s - w^d_u)}_{\text{Net expected innovative skill premium in country } d} - \underbrace{(w^o_s - w^o_u)}_{\text{Innovative skill premium at home}}.
\end{aligned} \quad (5)$$

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

$$G(\Gamma_s^d)E(\Gamma_s^d - M^d | M^d < \Gamma_s^d) + w_s^o = G(\Gamma_p^d)E(\Gamma_p^d - M^d | M^d < \Gamma_p^d) + w_p^o, \tag{6}$$

which can be rearranged as

$$G(\Gamma_s^d)E(\Gamma_s^d - M^d | M^d < \Gamma_s^d) - G(\Gamma_p^d)E(\Gamma_p^d - M^d | M^d < \Gamma_p^d) = w_p^o - w_s^o. \tag{7}$$

Let $\varphi(\Gamma_k^d) \equiv G(\Gamma_k^d)E(\Gamma_k^d - M^d | M^d < \Gamma_k^d)$. Noting[4] 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

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

Proof. See the Appendix. □

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 $w_u^d > w_s^o$,

[4] For the proof, see the Appendix.

where unskilled workers in the destination earn more than scientific workers in the origin country.[5]

2 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 test for crowding out of natives by immigrants, and to estimate the effect of immigrants on patenting per capita, including any positive spill–overs.

2.1 Individual–level data

A measure of the increase in patenting per capita owing to skilled immigrants can be calculated as follows. 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 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

$$\frac{1+\frac{\Delta P^{MS}}{P}}{1+\frac{\Delta M^S}{POP}} - 1 = (0.01)\frac{\alpha_0-\alpha_1}{\alpha_1(1-\alpha_1)}. \tag{8}$$

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

[5] 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.

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:

$$P(patent_j) = \beta_0 + \beta_1 IM_j + X_j\beta_2 + \epsilon_j, \tag{9}$$

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.

2.2 State–level data

We supplement the analysis using a panel of U.S. states with decennial data from 1950–2000. By extending the period of observation back to 1950, we are able to distinguish long run and short run effects by differencing the data in lengths varying from ten to 50 years.[6] We do not extend the data to prior decades as patenting in the years of the Great Depression and the Second World War was probably atypical.

In order to obtain an estimate of the impact of immigrants on innovation that encompasses both their own inventions and any positive spill–over effects, we estimate

$$\Delta log\ \frac{P_{i,t+1}}{POP_{i,t+1}} = \gamma_0 + \gamma_1 \Delta I^S_{it} + \gamma_2 \Delta N^S_{it} + \Delta X_{it}\gamma_3 + \gamma_4 Z_{i,1950} + \mu_t + \Delta\eta_{it}, \tag{10}$$

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 is the corresponding share for natives, $Z_{i,1950}$ are characteristics of the state in 1950, 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.

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

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 1950 (including land area), as the other covariates do not appear 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 fields. To capture potentially differential effects of this by state, we include among the X's the share of employment in electrical engineering–related fields in 1980, interacted with year dummies.[7] We use state populations to weight the regressions,[8] since in some small states one company drives the time series of patenting,[9] and we cluster standard errors by state to allow for serial correlation.

Because we account for state fixed effects by estimating 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.[10]

Equation (10) 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

[7]We use 1980 values as electrical engineering employment was still tiny in most states in 1950–1970.

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

[9]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.

[10]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.

in least squares estimation. On the other hand, $\hat{\gamma}_1$ in particular could be biased towards zero owing to measurement error.[11] We use several sets of instruments to address these problems for skilled immigrants. To instrument $\Delta I^S = I^S_t - I^S_{t-k}$, we use I^{HSD}_{t-k}, the share of the population that is an immigrant high school dropout at time $t-k$, and its square. The presence of immigrant high school dropouts in a state will mean the existence of cultural amenities attractive also to skilled immigrants. On the other hand, high school dropouts should play a minimal role in innovation, justifying their exclusion from equation (10). A (preferred) variant of this instrument set is three variables for the share of high school dropouts at $t-k$ who were born in Europe, China and India, the most common source regions for skilled immigrants. Alternatively, we use the values of the variables at time $t-k-10$ as instruments so as to be more confident that they are unaffected by unobserved factors influencing the change in patenting between $t-k$ and t.[12]

We also use the state panel to test for crowd–out of natives, which if present would bias upward the impacts calculated using both the individual–level and state–level data. Natives may choose not to enter careers in science and engineering, or to work less, or to avoid certain states, owing to competition from immigrants whose comparative advantage is in less language–intensive and less institution–specific occupations. Any drop in native inventors must be taken into account when calculating the net benefit of immigrants. We test for crowd–out using the approach of Card (2005) by running the regression

$$\Delta S_{it} = \delta_0 + \delta_1 \Delta I^S_{it} + \delta_2 \Delta Age_{it} + \mu_t + \Delta\nu_{it}, \tag{11}$$

where S is the share of the population or workforce (aged 18–65) composed of skilled natives and immigrants, I^S is again the share of skilled immigrants, and Age is the average age of the state's population between 18 and 65. We control for the average age

[11]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 may also be measurement error for the share of immigrant scientists and engineers in all years.

[12]For ΔN^S (native skilled workers), we have experimented unsuccessfully with lagged college enrollments as an instrument. The enrollment data only begin in the 1970s in any case.

of the state since birth cohort is the strongest determinant of schooling. If increases in the skilled immigrant share translate into one for one increases in the total skilled share, there is no crowd–out and $\hat{\delta}_1 = 1$. Complete crowd–out would be represented by $\hat{\delta}_1 = 0$, while $\hat{\delta}_1 > 1$ would indicate that skilled natives were attracted to states with many skilled immigrants. Measurement error could cause $\hat{\delta}_1$ to be biased towards zero.

It seems reasonable to think that the change in the share of less skilled immigrants would affect the share of the population that is skilled. We therefore do not use the instrumental variables described above which are based on shares of unskilled immigrants (the instruments would be correlated with the error term), but rather extend the covariates to include the change in the share of the population which is foreign–born with a high–school degree or less.

3 Data and Descriptive Statistics

3.1 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.[13] The survey will not capture patents by those with less than a college degree, but we assume that most patents are captured. The Data Appendix 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 con-

[13]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.

sistency 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, and 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), 1.8% of immigrants were granted patents compared to 0.9% of natives, a ratio of 2.0, and patents per capita were 0.054 for immigrants and 0.028 for natives, a ratio of 1.9. 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: 1.1% immigrants had commercialized a patent compared to 0.6% for natives, and commercialized patents per capita were 0.027 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, 6.1% immigrants in the latter sample had been granted a patent, compared to 4.9% natives, and immigrants hold 1.32 times the patents per capita of natives. Appendix Table 1 contains the means of variables used in the regression analysis below.

3.2 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 the Data Appendix 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 1951-2001, our principal 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). 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 (top line) and the inequality of counts without California (middle line).[14]

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.[15] 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 the Data Appendix 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, to calculate the average age of the state's population and to obtain weekly wages, we use the IPUMS microdata of the decennial censuses. We base most calculations on the population or workforce aged 18–65. Post–college education is the highest education level that can be measured consistently throughout 1950–2000. We define immigrants to be the foreign born. Information for

[14]Papers such as Co et al. (2006) have previously noted cross–state convergence in patents per capita.
[15]We are very grateful to Bill Kerr for making this extract for us.

Alaska and Hawaii is not available in 1950.

The variable means for the full 1950–2000 sample, weighted by population, are reported in Table 2. Between 1950 and 2000, the share of the population 18–65 composed of immigrants with college education or more increased eightfold to 3.5%, while the equivalent share for post–college increased eightfold to 1.6%. The population shares comprising natives with at least college and with post–college increased from 6.2% to 20.0% and from 2.3% to 7.7% respectively. The share of workers composed of immigrant scientists and engineers multiplied ninefold to 0.9%, while the native share rose from 1.2% to 3.5%. The Appendix Table 2 contains the means of the variables used as instruments.

4 Results

4.1 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 (8). 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 (=0.108/0.054) 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 $3.2 \times 6.1 = 19.5\%$.

To assess the reasons for the immigrant patenting superiority, 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 6.0% 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 with the aid of a probit for the probability of patenting. Column 1 shows that immigrants are 0.9 percentage points more likely to have been granted a patent in the sample of college graduates (top panel), 2.1 percentage points more likely in the sample of post–college educated (second panel) and 1.2 percentage points more likely in the sample of scientists and engineers (third panel). In the second column, we control for 30 dummies for the field of study of the highest degree obtained by the respondent. For all three samples, the gap becomes small and insignificant (5–7% of the original size for college and post–college graduates). 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: immigrants are a statistically significant 0.9–1.0 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.[16] In columns 5 and 6 we show that the same conclusions may be drawn for the probability of commercializing or licensing a patent.

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

4.2 Crowd–out

To test for crowd–out, we estimate equation (11). The results with college or more as an indicator of skill are reported in Panel A of Table 5. Column 1 shows that with weighted least squares and ten–year differences, a one percentage point increase in the share of the population that is immigrant college graduates only increases the overall share of college graduates by 0.51 percentage points. This indicates crowd–out, though the coefficient is not statistically significantly different from one. As we increase the length of the differences, evidence of crowd–out disappears: the coefficient is 0.75 for 30–year differences in column 2, and 0.95 for 50–year differences in column 3. In columns 4–6, we report the corresponding results after controlling for the change in the share of the population which is foreign–born with a high–school diploma or less. This addition increases the coefficient on the change in skilled immigration to 0.79 for ten–year differences (column 4), and to 1.2 for 30 and 50–year differences (columns 5 and 6), with none of the coefficients significantly different from one. The specifications of columns 4–6 are preferred to those of columns 1–3, so the preferred point estimates indicate at most about 20% crowd–out.

In panel B, we repeat the regressions using post–college education as the measure of skill. The coefficients in all columns are significantly greater than one, suggesting that skilled natives are attracted to states (or education levels) with many immigrants. In panel C, we repeat the regressions using the share of workers who are scientists and engineers. The coefficients indicate no (columns 1 and 3–6) or little (column 2) crowd–out, with none of the point estimates significantly different from one.

We have repeated all the regressions including dummies for seven BEA regions and the results change little, except that the coefficient when skill is measured by a college degree falls back to 0.55 for ten–year differences (the coefficient is 0.92 for the unreported 20–year differences). In summary, with the exception of one coefficient, there is no evidence of crowd–out, and for post–graduates it appears that natives attract immigrants.

4.3 State determinants of patenting

In Table 6, we estimate the state determinants of patenting using differences of different lengths, with a college degree as the measure of skill. In columns 1–4 the dependent variable is the log of patents per capita. The coefficients on the share of immigrant college graduates are positive and significant. In columns 1–3, where we use weighted least squares, a one percentage point increase in the share of the population composed of immigrant college graduates is associated with an 11–12% increase in patenting for ten and 30 year differences, and a 15.6 log point (17%) increase for 50 year differences. These effects are larger than the 6% impact calculated based on the NSCG data, implying positive spill–over effects of immigrants.

In column 4, we present the results of instrumenting the ten–year change in skilled immigrant share with the share of European, Chinese and Indian high–school dropouts at $t-10$ (the initial year of the pair of years differenced). The coefficient on the change in the immigrant share is a statistically significant 17.7, and larger than its least squares counterpart of 11.4 in column 1 (though not statistically significantly so). This 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. Another possibility is that the instrumental variables estimators place more weight on later years of the sample when the effects seem to be higher. It seems less likely that skilled immigrants whose behavior is affected by the instrument (skilled immigrants whose location decision is affected by the presence of other immigrants) are more inventive than other immigrants. We do not present instrumental variables estimates for longer differences for this or most later specifications: results are generally similar for 20–year differences, whereas for 30–50 year differences the instruments are not strong in the first stage.

In columns 5–7 the dependent variable is simply the change in patents per capita (in these columns the coefficients are multiplied by 100). The least squares effects for ten and 50–year differences are similar: a one percentage point increase in the skilled immigrant share is associated with a 0.000039 increase in patents per capita, which is a 17% increase compared to the mean. The corresponding impact for the unreported 30–year differences is 13%, so the results are similar to those of the log specification in columns 1–3. The instrumental variables coefficient in column 7 is larger than its least squares counterpart in column 5, but insignificant. The skilled immigrant coefficients in columns 5–7 are not very sensitive to the covariates included, while the results in columns 1–4 are much smaller if the 1950 covariates (and land area) are not included.

By contrast, most of the coefficients on the change in the share of native college graduates are small and insignificant. The point estimate increases as the difference length increases, and for 50–year differences the coefficient is a significant 6.7 in column 3 (about half the immigrant effect, as in the NSCG). As the share of native college graduates changes only gradually (i.e. at low frequency), the absence of significance at short differences probably reflects the emphasis of short differences on high–frequency events (Baker, Benjamin and Stanger 1999). 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%.

Older populations appear to be more innovative, as indicated by the positive coefficients on the average age of the state in the log specifications of columns 1–4. 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 in the log specifications, presumably in part because military invention is primarily protected by secrecy rather than patents. Finally, the importance of the 1950 conditions (and land area) increases with the difference length.

These regressions are repeated in Table 7 with post–college education (panel A) and a science and engineering occupation (panel B) as measures of skill. The least squares coefficients for immigrant post–college range from 17–27 in columns 1–3, where the dependent variable is in logs. These estimates are almost twice as high as for immigrant college graduates in Table 6, consistent with the NSCG data. The ten–year difference instrumental variables coefficient in column 4 is higher, at 38.1, but statistically insignificant. The coefficients in columns 5–6 are insignificant, but are also about double their counterparts in Table 6. The instrumental variables coefficient in column 7 is larger than its least squares counterpart in column 5, but also insignificant. The coefficients on the share of native post–college educated are never statistically significant, though the point estimates are higher for the longer differences. The immigrant/native ratio at 50–year differences is 2.8–3.3, compared to 3.0 in the NSCG.

In panel B, the coefficients are significant in all columns for immigrants and most columns for natives, and are larger than for the other skill groups. For immigrants in columns 1–3, a one percentage point increase raises patents by 48–59 log points, or 62–80%. Unlike for college graduates and post–college educated, the instrumental variables estimates (columns 4 and 7) are fairly similar to the least squares estimates (columns 1 and 5). The coefficients are high compared with the direct NSCG effect of about 19.5% and compared with that of natives at 50–year differences (29 log points), given that in the NSCG the immigrant patenting advantage over natives was only 32% amongst scientists and engineers. However, the discrepancy is smaller in the specification we present below as our preferred specification.

We have repeated all the least squares regressions of Tables 6 and 7, splitting the skilled natives according to whether they lived in the state of their birth or not (these results are not reported). For short differences, the coefficients on the change in the share of both skilled native groups are small, for all three skill measures. As the difference length increases, it is the coefficient on the change in the share of skilled natives born in another state that increases.

In Table 8 we present various alternative estimates of the effects of skilled immigrants, concentrating on the college–educated and the scientists and engineers, on ten-year differences, and on the log specification (results without logs display similar patterns). We report only the coefficient on the change in the skilled immigrant share, each from a different regression. In the first row, we reproduce the baseline least squares and instrumental variables results from Tables 6 and 7. In the next three rows, we vary the instruments used. In the second row we use as instruments the shares of the population composed of

European, Chinese and Indian high school dropouts at $t - 20$, instead of at $t - 10$ as in the baseline. The resulting coefficients are slightly larger than the baseline instrumental variables coefficients, which in turn were higher than the least squares results. In rows 3 and 4, we use as instruments the share of all foreign–born high school dropouts and its square, at $t - 10$, and at $t - 20$. With these instruments, the point estimates are quite similar to the baseline least squares results for college graduates, but for scientists and engineers are slightly higher than the baseline instrumental variables results.

In the next two rows we experiment with adding covariates. In row 5 we allow for (seven) BEA–region specific trends in patents per capita. This reduces the coefficients to 68–84% of the magnitudes of the baseline row and renders them statistically insignificant, though the least squares coefficients are significant at the 10% level. In row 6, we add instead the interactions of the 1980 share of employment in electrical engineering–related sectors interacted with year dummies. This yields estimates that are also lower than those in the baseline row, though generally statistically significant, this time 79–86% of the baseline magnitudes.

In row 7 we investigate the influence of California in the baseline specification by dropping that state. This reduces the estimates greatly. Finally, we assess the robustness to dropping the 1990–2000 differences (while retaining California), using the baseline specification. This causes the weighted least squares coefficients to become much smaller and insignificant, with point estimates of 6.5 and 21.2 in columns 1 and 3. However, for the college educated, the larger instrumental variables estimate of 12.5 is statistically significant in column 2. Instrumental variables point estimates are also much larger than least squares estimates for scientists and engineers. The sensitivity to the dropping of the year 2000 is present at all lengths of differences (these results are not reported). The coefficient on the change in the share of skilled natives, by contrast, is not greatly affected by the dropping of the year 2000 (these results are also not reported). The influence of the year 2000 for immigrants reflects either a genuine change in the effect (perhaps caused by an increase in the quality of skilled immigrants through the expansion of the H–1B cap), reduced measurement error owing to larger numbers of skilled immigrants in the census, or the presence of a confounding factor correlated with increases in skilled immigrants in the 1990s. The results are not sensitive to the dropping of the 1980–1990 changes (these results are not reported).

Our preferred specification is the instrumental variables specification of row 6 in Table 8, which includes controls for the importance of electrical engineering in the state economy: instrumental variables estimation is preferred to least squares, the instrument using specific ethnicities is preferred to the instrument based on the share of all immigrant dropouts, and some controls for what is driving the growth in patents in recent years are desirable. A similar justification could be made for the specification of row 5, where regional trends are accounted for (and the results are similar to those of row 6). The preferred specifications mean that a one percentage point rise in the share of immigrant college graduates increases patenting per capita by 14 log points (15%), the same rise in the share of immigrant scientists and engineers increases patenting per capita by 45 log points (57%), and the same rise in the share of immigrant post–college educated increases patenting per capita by 27 log points (31%; this coefficient is not reported in the table). These effects imply large spill–overs, as they are considerably larger than the impacts calculated with the individual data of 6%, 12% and 19.5% for a one percentage point increase in immigrant college graduates, post–college graduates and scientists and engineers respectively.

In Table 9 we investigate further using the Harvard Business School patent data for 1971–2001. We report only the coefficient on the change in the skilled immigrant share, each from a different regression, with log patents per capita as the dependent variable. In the odd columns we use the preferred instrumental variables specification of row 6 in Table 8, while in the even columns we use the 20–year difference counterpart, as these results are more statistically significant. In row 1, we repeat the row 6 Table 8 regressions with the reduced number of years available, to serve as a benchmark: the results are similar. In row 2, we use patent citations, or quality–adjusted patents, instead of patent counts. The point estimates do fall slightly: immigrants are slightly less beneficial than they appear from the raw patent counts. This is consistent with the NSCG there was a slightly lower immigrant patenting advantage for commercialized or licensed patents than for all patents (see Table 1).

In the remaining rows 3–8, we examine patent counts for six different categories of patent. Splitting patents into categories increases the standard errors considerably, and most coefficients are insignificant. However, the the results do suggest a large impact of skilled immigrants on computer and communications patents (row 3), and no positive impact on drug and medical patents (row 5) and "other" patents (row 8).

5 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 1950–2000. A calculation for 1990–2000 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 increased patenting per capita by about 20%.[17] The 0.7 percentage point increase in the share of post–college immigrants increased patenting per capita by about 21%[18], and the 0.45 percentage point increase in immigrant scientists and engineers increased patenting per capita by about 22%.[19] 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.[20] We do not find evidence that immigrants crowd out natives from certain occupations or states.

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 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

[17] $14 \times 1.3 = 18.2$ log points$= 20\%$.

[18] $27 \times 0.7 = 18.9$ log points$= 21\%$.

[19] $45 \times 0.45 = 20.3$ log points$= 22\%$.

[20] $6.1\% \times 1.3 = 7.9\%; 12.2\% \times 0.7 = 8.5\%; 19.5\% \times 0.45 = 8.8\%$

recently than observably similar native scientists and engineers. Despite this, the fact that immigrants increase patenting per capita without reducing native patenting shows that their presence in the United States provides a previously undocumented 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.

If natives are making optimal career decisions, subsidies to induce them to enter science and engineering in greater numbers would not be beneficial even if the marginal native had higher patenting ability than immigrants in science and engineering. Policies to encourage natives to enter science and engineering are warranted only if they address obstacles to optimal decision–making, such as a lack of information about available careers, inadequate primary and secondary education or excessively high discount rates. The results do not make clear precisely which immigration policies are appropriate to take advantage of the contributions of immigrants demonstrated in the paper. While allocating more visas based on whether the applicant has studied science or engineering may seem appealing, such a policy ignores potential benefits of immigrants without a science or engineering background. Furthermore, admitting scientists and engineers on work visas should be weighed against an alternative of admitting foreign students to study science and engineering at U.S. universities.

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Appendix

A.1 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 (4) and (5) in (6). This gives

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

Using (3) and rearranging, we get

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

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

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

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:

$$\underbrace{\underbrace{(w_p^o - w_s^o)}_{\leqslant 0,\text{ since }\Gamma_p^d > \Gamma_s^d} \quad \underbrace{[1 - G(\Gamma_p^d)]}_{\geqslant 0,\text{ since }G(.)\text{ is a density}}}_{\leqslant 0} + \underbrace{\phi(\Gamma_s^d) - \phi(\Gamma_p^d)}_{\leqslant 0,\text{ since }\Gamma_p^d > \Gamma_s^d}$$
$$+ G(\Gamma_p^d)\max\{0, P_{pp}(w_p^d - w_u^d) - C_p^d\} \underbrace{-G(\Gamma_s^d)P_{ss}(w_s^d - w_u^d)}_{<0,\text{ else, no one wants skilled job}}.$$

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.2 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

$$\begin{aligned}\varphi(\Gamma_k^d) = G(\Gamma_k^d)E(\Gamma_k^d - M^d | M^d < \Gamma_k^d) &= \int_{M_L^d}^{\Gamma_k^d} (\Gamma_k^d - M^d) g(M^d) dM^d \\ &= \Gamma_k^d \underbrace{\int_{M_L^d}^{\Gamma_k^d} g(M^d) dM^d}_{G(\Gamma_k^d)} - \underbrace{\int_{M_L^d}^{\Gamma_k^d} M^d g(M^d) dM^d}_{\phi}\end{aligned}$$

$$\begin{aligned}\partial\varphi(\Gamma_k^d)/\partial\Gamma_k &= G(\Gamma_k^d) + \Gamma_k g(\Gamma_k^d) - \underbrace{\partial\phi/\partial\Gamma_k^d}_{=\Gamma_k g(\Gamma_k^d) \text{ using Fundamental Theorem of Calculus}} \\ &= G(\Gamma_k^d) \geq 0, \text{ since G(.) is a density function}\end{aligned}$$

□

Data Appendix

B.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. Immigrants are 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/.

B.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 my 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.

B.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 1950–1980 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 1950–1980 censuses, and a post–college degree in 1990 and 2000. This is the highest level of education that can be distinguished for the whole 1950–2000 period. We use the 1940 census to compute lagged instruments. Alaska and Hawaii are not in the 1940 and 1950 IPUMS. The SIC codes we count as electrical engineering are 321, 322, 342, 350, 371, 372.

B.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 my 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 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	0.018	0.009	0.034	0.013	0.061	0.049
Number patents granted	0.054	0.028	0.108	0.036	0.174	0.132
Any patent commercialized	0.011	0.006	0.020	0.008	0.036	0.030
Number patents commercialized	0.027	0.017	0.052	0.019	0.082	0.074
Share immigrant	0.144		0.166		0.245	
Observations	21,248	71,304	12,042	30,460	6840	15,519

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 patents and aggregate variables affecting patenting

	1950-2000	1950	2000
Patents/population, x100	0.023	0.018	0.035
	(0.015)	(0.011)	(0.020)
Share of population 18-65 that is:			
Immigrant, college education and above	0.016	0.004	0.035
Native, college education and above	0.136	0.062	0.200
Immigrant, post-college education	0.008	0.002	0.016
Native, post-college education	0.054	0.023	0.077
Share of workers 18-65 that are:			
Immigrant, scientists and engineers	0.004	0.001	0.009
Native, scientists and engineers	0.024	0.012	0.035
Population (millions)	9.7	6.2	12.5
	(7.8)	(4.3)	(10.1)
Age of population 18-65	38.8	38.7	39.5
	(1.0)	(0.9)	(0.6)
DoD prime military procurement contracts	3221	1500	5499
(millions of nominal $)	(4379)	(1679)	(5799)
State personal income per capita (nominal $)	13,160	1504	29,845
	(11005)	(317)	(4080)
Land area (millions of square kilometers)	0.193	0.174	0.209
	(0.171)	(0.152)	(0.183)
Observations	304	49	51

Notes: Means of state-level variables, weighted by state population the year after the census. Patents and population are led by one year. Census information is not available for Alaska and Hawaii in 1950. Patents are classified by year filed.

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	0.076	0.036
Biological, agricultural and environment sciences	0.023	0.011	0.056	0.040
Physical sciences	0.066	0.038	0.035	0.017
Social and related sciences	0.004	0.002	0.091	0.108
Engineering	0.060	0.042	0.132	0.053
Other S&E (mainly health)	0.007	0.004	0.164	0.121
Non-S&E	0.004	0.002	0.446	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), 92,552 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	**0.0089**	0.0006	**-0.0009**	-0.0006	**0.0055**	-0.0005
	(0.0009)	(0.0005)	**(0.0004)**	(0.0003)	**(0.0007)**	(0.0003)
Pseudo-R^2	0.01	0.15	0.19	0.21	0.01	0.18
Post-college graduates	**0.0214**	0.0012	0.0003	0.0004	**0.0127**	0.0001
	(0.0018)	(0.0007)	(0.0006)	(0.0005)	**(0.0014)**	(0.0004)
Pseudo-R^2	0.02	0.21	0.24	0.26	0.02	0.21
Scientists and engineers	**0.0117**	0.0020	**-0.0101**	**-0.0080**	0.0054	**-0.0056**
	(0.0038)	(0.0030)	**(0.0026)**	**(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, age2, sex, employed	--	--	--	Y	--	--

Notes: Marginal effect on dummy for foreign-born from weighted probits. There are 92,552 observations in the college graduate sample, 42,502 in the post-college sample and 22,359 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 (I combine the two S&E teacher training categories into one). Standard errors are in parentheses.

Table 5: Crowd-out - effect of change in immigrant skilled share on change in total skilled share

	(1)	(2)	(3)	(4)	(5)	(6)
		Basic specification			Control for less skilled immigration	
Difference:	10 year	30 year	50 year	10 year	30 year	50 year
Panel A: Immigrant college+ as share of population						
Δ % Immigrant	0.51	**0.75**	**0.95**	**0.79**	**1.22**	**1.23**
	(0.32)	**(0.38)**	**(0.35)**	**(0.24)**	**(0.27)**	**(0.29)**
	[0.13]	[0.52]	[0.88]	[0.39]	[0.42]	[0.44]
R-squared	0.69	0.52	0.33	0.72	0.63	0.50
Panel B: Immigrant post-college as share of population						
Δ % Immigrant	**1.42**	**1.50**	**1.88**	**1.74**	**2.02**	**2.08**
	(0.25)	**(0.48)**	**(0.33)**	**(0.16)**	**(0.23)**	**(0.23)**
	[0.11]	[0.30]	[0.01]	[0.00]	[0.00]	[0.00]
R-squared	0.80	0.38	0.58	0.84	0.60	0.75
Panel C: Immigrant scientists and engineers as share of workers						
Δ % Immigrant	**1.01**	**0.79**	**1.37**	**1.13**	**1.10**	**1.51**
	(0.29)	**(0.35)**	**(0.34)**	**(0.25)**	**(0.33)**	**(0.38)**
	[0.98]	[0.56]	[0.27]	[0.61]	[0.76]	[0.19]
R-squared	0.74	0.42	0.45	0.74	0.46	0.48
Observations	253	151	49	253	151	49

Notes: The dependent variable is the change in the share of skilled people across periods ranging from ten to 50 years: in panel A skilled people are college graduates (as a share of the population), in panel B post-college educated (as a share of the population), in panel C scientists and engineers (as a share of workers). Regressions are weighted with weights $1/(1/pop_t+1/pop_{t-k})$, where k is equal to 10 in columns 1 and 4, 30 in columns 2 and 5, and 50 in columns 3 and 6. All regressions also include change in average age and (except columns 3 and 6) year dummies. Regressions in columns 4-6 include the change in the share of immigrants with high school education or less as a share of the population. Standard errors clustered by state are in parentheses. P-value of the test that the coefficient is equal to one is in square brackets.

Table 6: Effect of share of immigrant college graduates on patents per capita

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ Log patents per capita				Δ Patents per capita		
	Weighted least squares			IV	Weighted LS		IV
Difference:	10 year	30 year	50 year	10 year	10 year	50 year	10 year
Δ % Immigrant college+	**11.4**	**11.7**	**15.6**	**17.7**	**0.389**	**0.387**	0.688
as share of population	**(4.1)**	**(3.0)**	**(4.8)**	**(7.6)**	**(0.173)**	**(0.186)**	(0.389)
				[16]			[16]
Δ % Native college+	2.1	**5.0**	**6.7**	3.3	-0.007	0.173	0.050
as share of population	(2.4)	**(2.0)**	**(2.6)**	(2.0)	(0.115)	(0.106)	(0.087)
Δ Age (average)	**0.119**	**0.147**	0.088	**0.120**	0.0023	-0.0019	0.0022
	(0.031)	**(0.049)**	(0.109)	**(0.032)**	(0.0013)	(0.0032)	(0.0014)
Δ DoD procurement	-0.031	**-0.090**	-0.063	**-0.039**	-0.0009	-0.0001	-0.0013
(log)	(0.016)	**(0.034)**	(0.074)	**(0.019)**	(0.0008)	(0.0024)	(0.0009)
Land area (log)	**0.071**	**0.207**	**0.404**	**0.078**	**0.0020**	**0.0101**	**0.0023**
	(0.012)	**(0.033)**	**(0.086)**	**(0.013)**	**(0.0005)**	**(0.0024)**	**(0.0006)**
Population 1950 (log)	**-0.049**	**-0.174**	**-0.300**	**-0.059**	**-0.0015**	-0.0076	**-0.0020**
	(0.015)	**(0.035)**	**(0.087)**	**(0.015)**	**0.0007)**	(0.0041)	**(0.0007)**
State personal income	**-0.184**	**-0.814**	**-1.483**	**-0.251**	0.0031	-0.0031	0.0001
per capita 1950 (log)	**(0.076)**	**(0.174)**	**(0.387)**	**(0.083)**	(0.0025)	(0.0114)	(0.0033)
R-squared	0.64	0.57	0.57	--	0.47	0.34	--
Observations	253	151	49	253	253	49	253

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 (columns 1-3, 5-6) or instrumental variables (columns 4 and 7) with weights $1/(1/pop_{t+1}+1/pop_{t-k+1})$, where k the length of the difference. Regressions in columns 1,2,4, 5 and 7 include year dummies. The instrumented variable is the change in the share of immigrant college graduates; the instruments are three variables for the share of high school dropouts in the population at time t-10 from Europe, China and India. F-statistic for test of joint significance of excluded instruments in the first stage in brackets. Standard errors clustered by state are in parentheses. Coefficients in columns 5-7 are multiplied by 100.

Table 7: Effect of immigrant post-college and scientist and engineer shares on patents per capita

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ Log patents per capita				Δ Patents per capita		
	Weighted least squares			IV	Weighted LS		IV
Difference:	10 year	30 year	50 year	10 year	10 year	50 year	10 year
Panel A: Immigrant post-college as share of population							
Δ % Immigrant	17.7	**21.4**	**27.4**	38.1	0.756	0.657	1.733
	(11.1)	**(8.2)**	**(11.5)**	(21.9)	(0.526)	(0.481)	(1.160)
				[16]			[16]
Δ % Native	-1.2	1.3	9.9	-2.2	-0.079	0.197	-0.125
	(3.3)	(4.4)	(6.8)	(3.6)	(0.148)	(0.289)	(0.172)
R-squared	0.63	0.52	0.52	--	0.46	0.29	--
Panel B: Immigrant scientists and engineers as share of workers							
Δ % Immigrant	**48.7**	**48.6**	**59.2**	**53.6**	**2.393**	**1.934**	**2.263**
	(20.7)	**(16.1)**	**(15.8)**	**(25.1)**	**(1.017)**	**(0.717)**	**(1.188)**
				[6]			[6]
Δ % Native	**11.8**	**20.8**	**29.5**	**11.7**	0.231	**0.866**	0.233
	(5.3)	**(6.9)**	**(7.8)**	**(5.3)**	(0.237)	**(0.287)**	(0.241)
R-squared	0.68	0.59	0.67	--	0.55	0.48	--
Observations	253	151	49	253	253	49	253

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 (columns 1-3, 5-6) or instrumental variables (columns 4 and 7) 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 6. The instrumented variable is the change in the share of skilled immigrants; the instruments are three variables for the share of high school dropouts in the population at time t-10 from Europe, China and India. F-statistic for test of joint significance of excluded instruments in the first stage in brackets. Standard errors clustered by state are in parentheses. Coefficients in columns 4-6 are multiplied by 100.

Table 8: Effect of skilled immigration on patents per capita - specification checks

	(1)	(2)	(3)	(4)
	Δ Log patents per capita, 10-year differences			
Skilled group:	College graduates		Scientists and engineers	
Δ % Immigrant	WLS	IV	WLS	IV
1. Base specifications	**11.4**	**17.7**	**48.7**	**53.6**
(Tables 6,7)	**(4.1)**	**(7.6)**	**(20.7)**	**(25.1)**
		[16]		[6]
2. Instrument is % population which is	--	**23.1**	--	**56.5**
European, Chinese, Indian-born high		**(8.4)**		**(23.8)**
school dropouts at t-20		[10]		[10]
3. Instrument is % population which is	--	10.4	--	**58.8**
foreign-born high school dropout at t-10,		(6.2)		**(22.7)**
and its square		[28]		[15]
4. Instrument is % population which is	--	10.6	--	60.5
foreign-born high school dropout at t-20,		(7.9)		(30.7)
and its square		[17]		[5]
5. Covariates include BEA region dummies	8.1	13.6	40.8	36.3
	(4.4)	(9.5)	(24.1)	(30.3)
		[24]		[7]
6. Covariates include % workers in	**9.8**	**14.0**	**41.5**	44.5
electrical sectors 1980*year dummies	**(4.0)**	**(5.9)**	**(18.1)**	(23.1)
		[14]		[5]
7. Sample without California	7.4	6.9	17.4	7.0
(248 obs)	(3.9)	(5.0)	(12.4)	(20.1)
		[19]		[6]
8. Sample without year 2000	6.5	**12.5**	21.2	72.2
(202 obs)	(3.4)	**(4.7)**	(16.4)	(41.7)
		[23]		[5]

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 (columns 1 and 3) or instrumental variables (columns 2 and 4) with weights $1/(1/pop_{t+1}+1/pop_{t-9})$. The instruments are three variables for the share of high school dropouts in the population at time t-10 from Europe, China and India unless otherwise specified. F-statistic for test of joint significance of excluded instruments in the first stage in brackets. All regressions also include the covariates of Table 6 including the appropriate differenced share of skilled natives. Standard errors clustered by state are in parentheses. 253 observations unless otherwise noted.

Table 9: Effect of skilled immigration on patent citations per capita and patents by type 1970-2000

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Log patents per capita, instrumental variables					
Skilled group:	College graduates		Post-college		Scientists/engineers	
Difference:	10 year	20 year	10 year	20 year	10 year	20 year
1. Patents	**13.5**	**18.0**	20.6	**38.6**	40.2	**54.5**
	(6.5)	**(3.7)**	(16.0)	**(12.9)**	(23.9)	**(21.1)**
2. Patent citations	7.4	**12.2**	15.5	22.0	34.5	**45.9**
	(8.0)	**(4.7)**	(21.0)	(11.6)	(26.2)	**(20.6)**
3. Computer and communications patents	21.8	**35.4**	23.1	**80.7**	35.0	63.1
	(11.7)	**(9.9)**	(26.9)	**(28.7)**	(34.4)	(35.5)
4. Electrical and electronic patents	17.5	**16.8**	26.2	37.0	25.8	45.7
	(10.5)	**(7.6)**	(23.1)	(21.6)	(36.9)	(31.4)
5. Drug and medical patents	3.2	-0.9	-19.1	-27.7	-0.7	12.7
	(12.7)	(11.8)	(28.4)	(33.2)	(35.0)	(39.7)
6. Chemical patents	9.1	**17.3**	0.7	31.2	1.0	28.0
	(8.8)	**(7.9)**	(19.9)	(20.8)	(29.4)	(25.0)
7. Mechanical patents	1.3	11.1	-5.8	32.4	-1.8	16.7
	(5.7)	(7.7)	(12.9)	(23.3)	(19.5)	(15.8)
8. Other patents	-4.6	0.2	**-15.4**	-6.2	-25.1	-20.1
	(3.3)	(4.1)	**(7.50)**	(11.9)	(12.8)	(13.0)
First stage F-statistic for excluded instruments	7	9	10	7	6	8
Observations (rows 1,2,7,8)	153	102	153	102	153	102

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 per capita across ten or twenty years, or log of patent citations per capita, with a lead of one year compared to the independent variables. Weighted instrumental variables for 1970-2000 with weights $1/(1/pop_{t+1}+1/pop_{t-k+1})$, where k the length of the difference. All regressions include the share of employment in electrical sectors in 1980 interacted with year dummies and the other covariates included in Table 6. The instrumented variable is the change in the share of skilled immigrants; the instruments are three variables for the share of high school dropouts in the population at time t-10 from Europe, China and India. Standard errors clustered by state are in parentheses. Observations for ten and twenty year differences are 141 and 95 for computer patents, 149 and 99 for electrical patents, 150 and 99 for drug patents, and 150 and 100 for chemical patents.

Appendix Table 1: 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, math	0.076	0.036	0.091	0.027	0.219	0.168
Biological, agri-cultural, environ-ment 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.

Source: National Survey of College Graduates

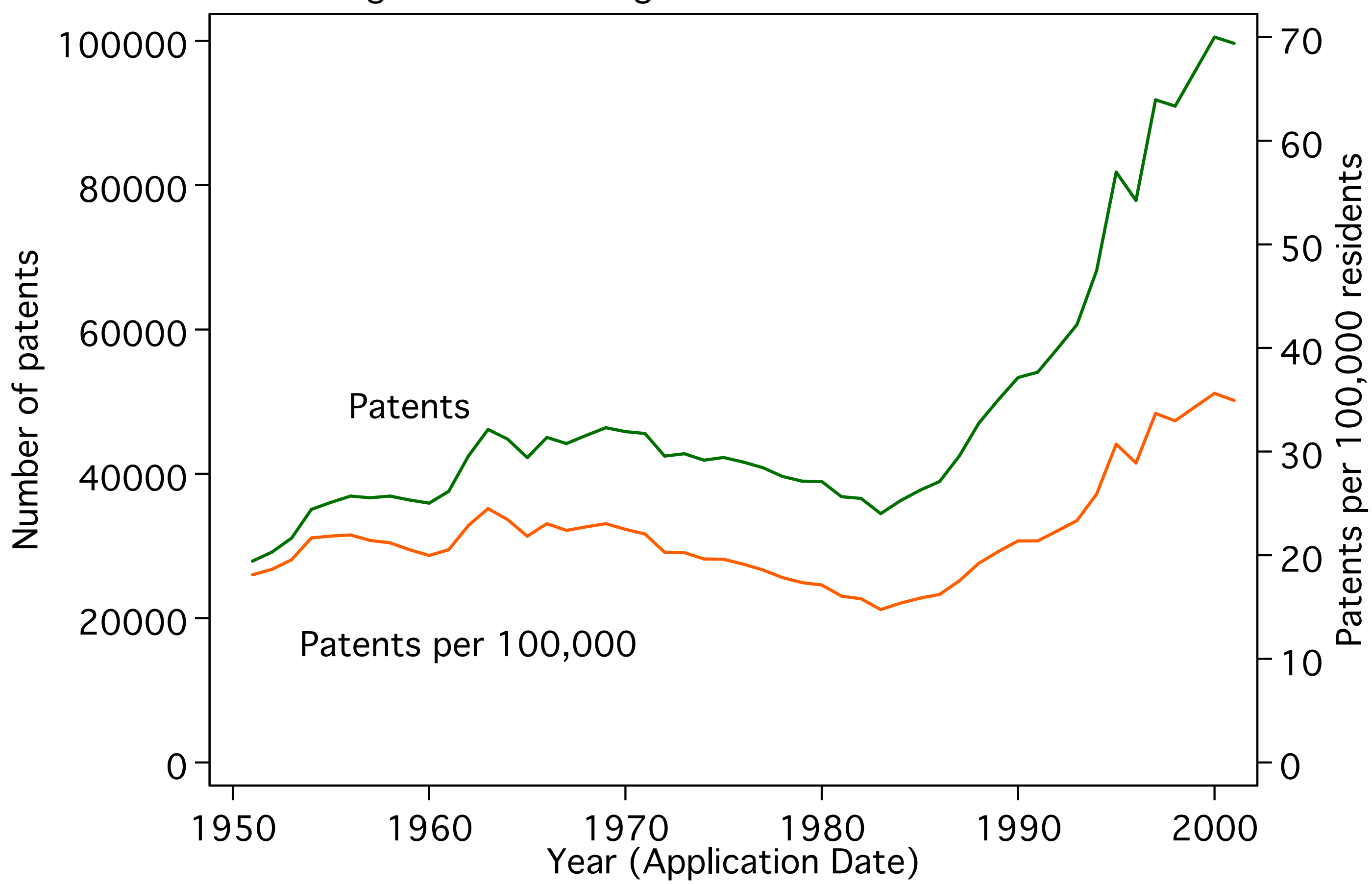
Appendix Table 2: Means of aggregate instruments for change in skilled immigrant share

	1950-2000	1950	2000
Share of population 18-65 that is:			
Immigrant, high school dropouts	0.041	0.066	0.046
Share of population 18+ that is:			
European-born, high school dropouts	0.023	0.067	0.004
Chinese-born, high school dropouts	0.0008	0.0006	0.0013
Indian-born, high school dropouts	0.0002	0.0000	0.0006
Observations	304	49	51

Notes: Means of state-level variables, weighted by state population. Census information is not available for Alaska and Hawaii in 1950.

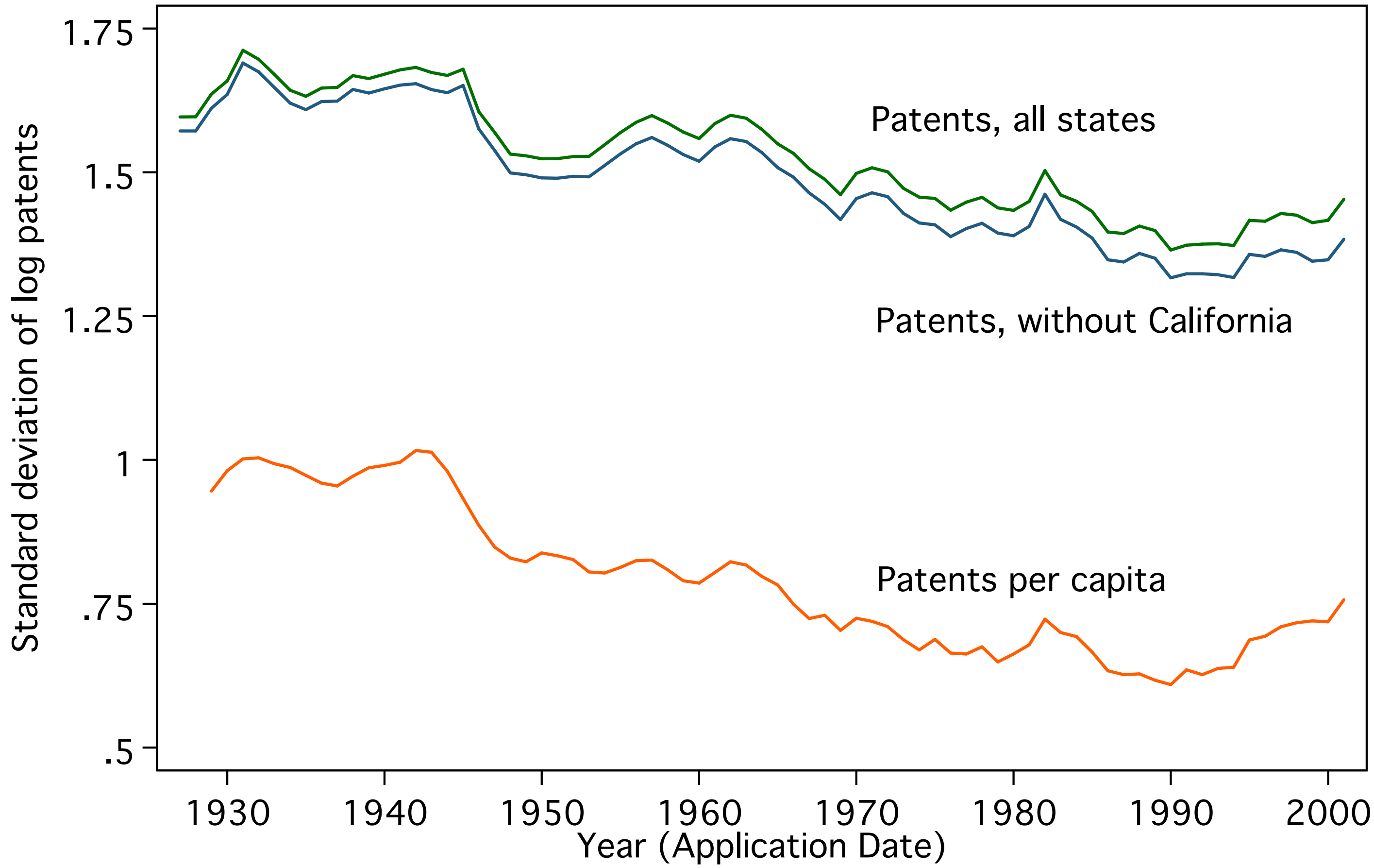
Source: U.S. Census Bureau, IPUMS decennial census microdata usa.ipums.org/usa/

Figure 1: U.S. Origin U.S. Patents 1951-2001



Source: USPTO, BEA and author's calculations

Figure 2: Convergence in Patenting Across States 1929-2001



Source: USPTO, BEA and author's calculations