Are They the Best and the Brightest?
Analysis of Employer-Sponsored Tech Immigrants

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Berkeley Center for Globalization and Information Technology
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The Setting

“[restrictive U.S. immigration policy is] driving away the world’s best and brightest”—Bill Gates, 2007

“We should not [send our] bright and talented international students...to work for our competitors abroad upon graduation”–NAFSA (Nat. Assoc. of Foreign Student Advisers)

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- But are most of those sponsored by the tech industry of that caliber?
- And for those who ARE of that caliber, is current policy reasonably welcoming?
Previous Work

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<td>highest quarter</td>
<td>37.2%</td>
</tr>
<tr>
<td>second quarter</td>
<td>44.5%</td>
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<td>third quarter</td>
<td>47.5%</td>
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<td>lowest quarter</td>
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Table: Foreign-student enrollments in Ph.D. engineering programs
Our Approaches

We will approach the question via analyses of:

- wages
- dissertation awards
- patents
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Wage Issues

Underpayment found to be 15-20% in (Matloff, 2003) and 33% in (Ong, 1997).

Due to loopholes, legally required prevailing wage is typically well below real market wage (Matloff, 2003).

Congressionally-commissioned employer surveys, (NRC, 2001) and (GAO, 2003), found many employers admitting to paying H-1B workers less than comparable Americans. GAO even noted role of loopholes: 

...[employers] hired H-1B workers in part because these workers would often accept lower salaries...however, these employers said they never paid H-1B workers less than the required wage.

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Solutions to Wage Issues

How does one use wages to assess talent, given underpayment of the foreign workers? One can:

- Use as baseline wage 20% above legal prevailing wage.
- Consider only workers who were originally sponsored by employers but now have green cards or citizenship.
- Consider nonmonetary evidence of outstanding talent, such as awards and patents.
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Enables analysis by employer and nationality.
Accounts for region via prevailing wage.
Lacks data on education, age.
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PERM Analysis

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$$WR = \text{median of actual wage emp. claimed prev. wg.}$$

By law, must have $$WR \geq 1.$$ But, denominator too small by factor of 1.15 to 1.33 (see above). So, only (median) values higher than, say 1.25, indicate a firm is hiring mainly the "best and brightest."
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Second Wage Analysis: 2000 Census Data

Looked at all programmers, software engineers and electrical engineers in California (not managers).

Proxy for employer sponsorship: Entered country after age 17.

Proxy for green card, cit.: Count those over 32, by which time most good (EB-1, EB-2) sponsored workers should have green cards.

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PUMS Analysis/Results

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Factor Impacts on Probability of Earning $> \$150K$

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MS, PhD: large positive impact
China: large negative impact
India: small positive or neutral (larger in linear regression of total wage)
other foreign: small positive or neutral
no evidence of overall “foreign genius”
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- Governments of China, Japan, S. Korea and Taiwan have all tried to remedy this.
- Language effects?
ACM Dissertation Awards

\[\text{names used as proxy}\]
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- Again, no evidence that the foreign students are outperforming the domestic ones.

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Final Remarks

Most of the sponsored foreign workers appear to be of ordinary talent. But again, some are indeed truly outstanding talents. We should facilitate the immigration of such talents.

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These slides, and the R programming code used to compile the statistics, are available at http://heather.cs.ucdavis.edu/BGIT.html