# Imputing the Legal Status of the Foreign Born Persons on Surveys: Two Approaches 

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## Motivation for Study

- States need estimates of size and characteristics of undocumented immigrants to implement federal health reform legislation
- Existing data sources on legal status are "thin"
- Question of how best to impute the legal status of foreign born persons in national surveys
- Study compares alternate methods


## The Foreign Born by "Status"

- Definitions are not necessarily common across entities
- (Authorized) Legal immigrants
- Naturalized (obtained citizenship)
- Lawful Permanent Resident (LPR; formally admitted status)
- Legal Temporary (a/k/a nonimmigrant)
- Application accepted; must have no violations
- Refugee/Asylee/Temporary Protected Status
- Granted this status but not yet converted to other status
- Unauthorized or Other
- Has or has not applied for any other status or status has not been granted yet


## A Simple Residual Method

- $F B=[L-(M+E)]+T+R$
- Where:
- $\mathrm{FB}=$ Total Foreign Born Population,
- L = Legal Immigrants,
- $M=$ Legal Immigrant Mortality,
- $\mathrm{E}=$ Emigration of Legal Immigrants,
- T = Temporary Migrants; and ,
- $R=$ Residual Foreign Born (Unauthorized or Quasi-Legal)
- Solve for R (the residual) after all other statuses have been identified
- Voila: We have a number for the unauthorized - the population of interest that does not exist in any other record


## Complaints About the Residual Method

- Using survey data for estimates can result in biases as the unauthorized do not necessarily want to respond to surveys (coverage)
- Administrative records are generated for other purposes thus may contain missing information or errors (e.g., LPR file and emigration)
- Other characteristics of interest do not necessarily "fall out" of residual methods
- Several assumptions (e.g. migration) may not hold
- Negative residuals


## A Model Based Approach

- The Survey of Income and Program Participation (SIPP) is a longitudinal survey primarily used to determine economic well-being
- Migration history is collected in topical module 2 including legal status at entry ("permanent", "refugee", "other") and if a status change occurred
- However, SIPP sample size is small relative to other surveys such as the American Community Survey (ACS)
- A technique to enhance the larger survey:
- Use logistic regression to predict legal status; estimate parameters for various demographic characteristics also found on other surveys
- Apply those parameter estimates to the larger survey
- Predict the foreign born person's legal status
- Target: "Not LPR or likely misreporting of citizenship status"


## Pros of the Model-Based Approach

- Take advantage of direct information -- No other Federal survey asks legal status of the foreign born
- Immigration status upon entry to the U.S.
- Change in status to permanent resident
- Then, take advantage of a much larger survey (American Community Survey) to impute the legal statuses estimated from the SIPP
- The model can be run in future SIPP panels to update the parameter estimates


## Cons of the Model Based Approach

- Public-use files collapse legal status categories
- Because the SIPP sample size is small, the number of cases of immigrants will be relatively small
- There is likely to be (downward) response bias in the migration questions


## Latent Class Analysis

- Latent Class Analysis (a/k/a finite mixture modeling) improves on simple "classical" clustering
- People in the same "cluster" share a common joint probability distribution among the observed variables estimated by maximum likelihood methods


## Pros of Latent Class Modeling

- Various diagnostics are available
- It allows the inclusion of exogenous variables
- It can be performed on variables that are measured on different scales
- Output is a probability (based on a probability model) rather than a fixed class assignment
- The clustering is testable against other methods
- E.g. multinomial logit analysis
- The results should be very similar


## Cons of Latent Class Modeling

- Conditional independence
- Choice of explanatory variables
- Model identification
- The data are allowed to do "all" the talking


## Estimation System Diagram



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## Problems to be Addressed

- Coverage of the foreign born on surveys
- Foreign born in general, and unauthorized foreign born in particular, are widely believed to be undercovered in surveys
- Resolved via 'control totals':
- Simple Rake Factor: Control only to total FB population
- Complicated Rake Factor: Control to broad age/sex categories
- Model specification, three approaches
- Analyst-driven RHS (SIPP)
- "Boosted" automatic interaction detection (Boosted SIPP)
- A variety of latent class models attempted
- Variance Estimation
- Not primary focus today, but if imputation independent of sample design, $\mathrm{V}(\mathrm{T})=\mathrm{V}(\mathrm{I})^{*} \mathrm{~V}(\mathrm{~S})$, where sample design variance is calculable, and model mean squared error can be taken as imputation variance


## An Overview of the Imputation Models

- SIPP: Left hand side "not LPR or likely misreport", Right hand side a collection of variables (year of entry, age, age-squared, 'hard-to-count' variables) likely to be predictive
- Boosted SIPP: Right hand side variables entered into automatic boosting program, unattended
- LC: Due to identifiability concerns, a limited set of hard-to-count variables


## Comparison of Results

- After probabilities are placed on individual records, totals by state/domain are calculated by summing probabilities
- If the approach has external validity, the results of the (various) modeling strategies should look reasonably similar on an aggregate basis
- If the results are similar to those generated by residual methods, the validity of each is enhanced
- Small-domain results should make demographic sense


## Comparison of Total Estimates to Each Other (1 of 2)

Table 1: Survey Total Estimates by state (Model 1-SRF,1-CRF,2-CRF,3-CRF,4-CRF, SIPP, and Boosted SIPP), based on 2009 ACS

|  | (LC1-SRF) | (LC1-CRF) | (LC2-CRF) | (LC3-CRF) | (LC4-CRF) | (SIPP) | (Boosted <br> SIPP) |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |  |  | Total |

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## Comparison of Total Estimates to Each Other (2 of 2)

| Missouri | 59,687 | 61,159 | 60,568 | 60,567 | 60,567 | 61,352 | 56,820 |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Montana | 4,526 | 4,501 | 4,595 | 4,595 | 4,595 | 4,433 | 3,847 |
| Nebraska | 36,809 | 39,422 | 38,487 | 38,487 | 38,487 | 40,216 | 39,723 |
| Nevada | 152,006 | 153,532 | 153,075 | 153,075 | 153,075 | 164,842 | 160,705 |
| New_Hampshire | 18,231 | 17,851 | 18,045 | 18,045 | 18,045 | 16,463 | 15,259 |
| New_Jersey | 441,543 | 444,570 | 436,008 | 436,004 | 436,004 | 444,634 | 427,844 |
| New_Mexico | 66,708 | 67,345 | 68,605 | 68,606 | 68,606 | 69,134 | 68,706 |
| New_York | $1,006,584$ | 968,245 | 950,415 | 950,412 | 950,412 | 926,298 | 914,987 |
| North_Carolina | 238,912 | 255,069 | 249,886 | 249,883 | 249,883 | 266,484 | 262,477 |
| North_Dakota | 5,786 | 5,905 | 5,732 | 5,732 | 5,732 | 6,492 | 5,331 |
| Ohio | 110,866 | 115,010 | 114,059 | 114,058 | 114,058 | 109,791 | 100,255 |
| Oklahoma | 63,481 | 67,420 | 67,415 | 67,415 | 67,415 | 72,102 | 71,137 |
| Oregon | 117,998 | 119,787 | 121,503 | 121,504 | 121,504 | 120,239 | 124,764 |
| Pennsylvania | 163,302 | 163,497 | 163,780 | 163,779 | 163,779 | 150,333 | 140,531 |
| Rhode_Island | 35,923 | 34,898 | 34,179 | 34,179 | 34,179 | 35,580 | 35,383 |
| South_Carolina | 71,773 | 75,644 | 73,696 | 73,695 | 73,695 | 84,884 | 78,565 |
| South_Dakota | 4,789 | 5,119 | 4,973 | 4,973 | 4,973 | 5,173 | 4,469 |
| Tennessee | 88,361 | 94,774 | 94,105 | 94,105 | 94,105 | 98,138 | 93,770 |
| Texas | $1,347,441$ | $1,370,619$ | $1,379,599$ | $1,379,603$ | $1,379,603$ | $1,418,183$ | $1,450,644$ |
| Utah | 68,551 | 72,520 | 74,017 | 74,017 | 74,017 | 72,127 | 73,349 |
| Vermont | 4,713 | 4,305 | 4,481 | 4,481 | 4,481 | 2,861 | 2,891 |
| Virginia | 220,842 | 225,510 | 224,088 | 224,087 | 224,087 | 226,234 | 206,909 |
| Washington | 220,420 | 224,261 | 224,469 | 224,469 | 224,469 | 212,192 | 207,814 |
| West_Virginia | 5,111 | 5,275 | 5,505 | 5,505 | 5,505 | 4,639 | 4,314 |
| Wisconsin | 73,594 | 77,210 | 76,734 | 76,733 | 76,733 | 78,528 | 75,997 |
| Wyoming | 5,173 | 5,548 | 5,544 | 5,544 | 5,544 | 5,213 | 5,067 |
| Observations | 171305 | 171305 | 171305 | 171305 | 171305 | 171305 | 171305 |

## Comparison of Total Estimates with Office of Immigration Statistics Residual Estimates

State of Residence of the Unauthorized Immigrant Population

OIS residual estimates

State of residence
Total
California
Texas
Florida
New York
Illinois
Georgia
Arizona
North Caroline
New Jersey
Nevada
Other states $\quad \mathbf{2 , 7 3 0 , 0 0 0}$
Detail may not sum to totals because of rounding.
Source: U.S. Department of Homeland Security.
Table 4.

| SIPP model-based estimates |  | Latent Class (model 1)based estimates |  | Boosted SIPP modelbased estimates |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | ACS 2009 |  |  |  |
| Total Estimate | Percent of total | Total Estimate | Percent of total | Total Estimate | Percent of total |
| 10,750,000 |  | 10,750,000 |  | 10,750,000 |  |
| 2,566,899 | 24\% | 2,579,640 | 24\% | 2,741,810 | 26\% |
| 1,418,183 | 13\% | 1,370,620 | 13\% | 1,437,921 | 13\% |
| 877,530 | 8\% | 852,209 | 8\% | 829,632 | 8\% |
| 926,298 | 9\% | 968,236 | 9\% | 919,174 | 9\% |
| 450,244 | 4\% | 471,309 | 4\% | 466,011 | 4\% |
| 323,882 | 3\% | 321,289 | 3\% | 317,099 | 3\% |
| 318,739 | 3\% | 311,002 | 3\% | 326,542 | 3\% |
| 266,484 | 2\% | 255,061 | 2\% | 261,586 | 2\% |
| 444,634 | 4\% | 444,557 | 4\% | 430,723 | \% |
| 164,842 | 2\% | 153,532 | 1\% | 160,574 | 1\% |
| 2,992,264 | 28\% | 3,022,544 | 28\% | 2,858,927 | 27\% |

## Comparison of Total Estimates with Office of Immigration Statistics Residual Estimates

## Country of Birth of the Unauthorized Immigrant Population

| OIS residual estimates |  |  | SIPP model-based estimates |  | Latent Class (model-1) based estimates |  | Boosted SIPP-based estimates |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | ACS 2009 |  | ACS 2009 |  | ACS 2009 |  |
| Country of birth | January 2009 | Percent of total | Total estimate | Percent of total | Total estimate | Percent of total | Total estimate | Percent of total |
| Total | 10,750,000 |  | 10,750,000 |  | 10,750,000 |  | 10,750,000 |  |
| Mexico | 6,650,000 | 62\% | 4,865,822 | 45\% | 4,583,566 | 43\% | 5,229,107 | 49\% |
| El Salvador | 530,000 | 5\% | 478,028 | 4\% | 438,653 | 4\% | 497,099 | 5\% |
| Guatemala | 480,000 | 4\% | 413,356 | 4\% | 347,778 | 3\% | 421,152 | 4\% |
| Honduras | 320,000 | 3\% | 243,045 | 2\% | 205,557 | 2\% | 240,414 | 2\% |
| Philippines | 270,000 | 2\% | 228,521 | 2\% | 269,011 | 3\% | 204,538 | 2\% |
| India | 200,000 | 2\% | 465,762 | 4\% | 493,209 | 5\% | 403,889 | 4\% |
| Korea | 200,000 | 2\% | 192,292 | 2\% | 220,526 | 2\% | 181,195 | 2\% |
| Ecuador | 170,000 | 2\% | 155,081 | 1\% | 135,270 | 1\% | 157,668 | 1\% |
| Brazil | 150,000 | 1\% | 133,521 | 1\% | 145,677 | 1\% | 118,446 | 1\% |
| China | 120,000 | 1\% | 290,833 | 3\% | 321,372 | 3\% | 266,022 | 2\% |
| Other Countrie | 1,650,000 | 15\% | 3,283,740 | 31\% | 3,589,380 | 33\% | 3,030,470 | 28\% |

Detail may not sum to totals because of rounding.
Source: U.S. Department of Homeland Security.
Table 3.

## Comparison of Total Estimates with Office of Immigration Statistics Residual Estimates

Period of Entry of the Unauthorized Immigrant Population

OIS residual estimates
Period of entry

| January | Percent of |
| :---: | :---: |
| 2009 | Total |

## All years

2005-2008
2000-2004
1995-1999
1990-1994
1985-1989
1980-1984


| SIPP model-based |  |
| :--- | :--- |
| estimates |  |
|  |  |
|  |  |
| ACS 2009 |  |
|  | Per |
| Total estimate |  |
| $10,750,000$ |  |
| $4,566,277$ |  |
| $2,913,867$ |  |
| $1,310,408$ |  |
| 821,096 |  |
| 572,967 |  |
| 278,452 |  |
| 286,933 |  |



[^0]Table 1.

## Prob[Nonpermanent] by age and Hispanic Ethnicity



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Graphs by Collapsed country of birth code
Note: Y-scale in 100,000's
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Graphs by Collapsed state codes
Note: Y-scale in 100,000's
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Graphs by Hispanic and non-Husband/Wife household
Note: Y-scale in 100,000's
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Graphs by Numeric sex code (1=Male, 2=Female) and 1-Digit Occupation
Note: Y-scale in 100,000's
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## Conclusions and Next Steps

- Model coefficients appear consistent with a priori beliefs about prediction of legal status (not presented today)
- Levels may not match exterior control totals; thus, an external rake may be needed; but once raked, results are consistent across models and with residual results (with some interesting differences, as well)
- Demographic outputs look promising
- A Bayesian approach (incorporating priors about levels) may be a good next step for modeling
- Finalize variance estimation
- Try the model-based method on other surveys
- Submit results to scientific scrutiny

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[^0]:    Source: U.S. Department of Homeland Security.

