Post-Release Employment of the Formerly Incarcerated: Labor Market Perspective

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Understanding employment outcomes for the formerly incarcerated

- Labor market perspective
  - Evaluate the performance of alternative models to classify the employment outcomes of the formerly incarcerated
  - Identify characteristics of formerly incarcerated that contribute to successful employment outcomes
  - Employment outcomes
    - Employed within 2 years of release
    - Established stable employment within 2 years of release
      - Three consecutive quarters of employment

Employment Outcomes for Formerly Incarcerated: Policy Imperative

- States experiencing severe labor shortages
  - State unemployment rates are at historical lows
    - Pool of available labor for employment has diminished in the last two years
      - Aging of the labor force as baby boomers move to retirement age
      - Restrictive US immigration policy
  - State claims for unemployment insurance (layoffs) have reached historical lows
    - Overall levels of claims
    - Claims as a percentage of jobs
- State policy response to severe labor shortages
  - States have begun to weigh the costs of incarceration against the need to address severe labor shortages
    - State of Maine has implemented an early release program for nonviolent offenders to either jobs (primarily in the state’s tourism industry) or education
    - Conditional commutation of sentences to target labor shortages in critical state industries

Employment Outcomes for Formerly Incarcerated: Policy Imperative

- Operational rationale
  - Enhancing human capital and establishing job-ready skills while serving time
    - prison-based reentry preparation (*)
      - learning to accept responsibility for changing their criminal behavior, addressing substance abuse and health or mental health issues, and reconnecting with family, community,
      - gaining the necessary education, learning new work skills, and reconnecting with employers.
    - Typical Exiter cohort from Illinois prisons approximately 30,000 per year, nearly ½ the size of a typical 4-year degree graduate cohort from all Illinois public universities
      - tremendous amount of attention to employability and tracking of employment outcomes for holders of 4-year degrees, including federal reporting requirements
      - Predominant attention on the formerly incarcerated related to first aforementioned goal, need to more fully integrate both sets of goals identified for reentry

IL Department of Corrections. 2006, “Inside Out: A Plan to Reduce Recidivism and Improve Public Safety”, Report from the Community Safety and Reentry Commission.

Employment Outcomes for Formerly Incarcerated: Policy Imperative

- Operational rationale
  - State Income Tax Gain
    - Annual state tax gain per cohort of formerly incarcerated from employment
      - State income tax 3.75% X $20,000 ($10/hour) X 30,000 cohort X stable threshold
    - State tax gain by stable employment threshold
      - Stable employment at 30%- $6.75 million
      - Stable employment at 50%- $11.25 million
      - Stable employment at 70%- $15.75 million
  - Costs per recidivism event(*)
    - Taxpayer costs- $40,987
    - Victimization costs- $57,418
    - Indirect costs- $20,432

IL Sentencing Policy Advisory Council. 2015, “The High Costs of Recidivism”.

Methodology: Labor Market Features
(see Appendix)

- Personal characteristics
  - race, gender, kids, education at admission, TABE math and reading (standardized scores reported at admission), age at release, jail time
- Value-added human capital during incarceration
  - earned time credit for education, earned time credit for obtaining GED, industrial training program participation
- Local Labor Markets
  - Cook vs Non-Cook, education composition of jobs by Cook neighborhood

Methodology: Labor Market Labels

- Employed within 2 years of release
  - Training set: Formerly incarcerated who were released in 2011Q1 – 2011Q4 and employed within 8 quarters of their release
  - Test set: Formerly incarcerated who were released in 2012Q1 – 2012Q4 and employed within 8 quarters of their release

- Established stable employment within 2 years of release
  - Training set: Formerly incarcerated who were released in 2011Q1 – 2011Q4 and employed for 3 consecutive quarters within 8 quarters of their release
  - Test set :Formerly incarcerated who were released in 2012Q1 – 2012Q4 and employed for 3 consecutive quarters within 8 quarters of their release

Methodology: Modeling Employment Outcomes

- Modeling the Classification of Employment Outcomes
  - Train and Test Classification Models
    - K Nearest Neighbors
    - Logit regression

- Modeling the impact of employment outcome predictors
  - Odds ratios – impact of personal characteristics, value-added human capital during incarceration, and local labor market features on the likelihood of
    - Employment
    - Stable employment

Findings:
Modeling the Classification of Employment Outcomes

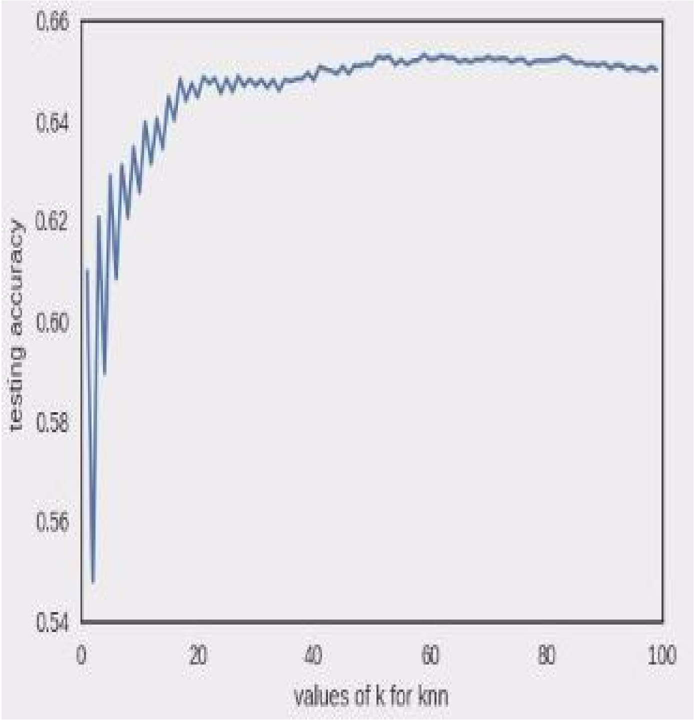
Training and Testing Classification Models

- K Nearest Neighbor Classification Model
  - An algorithm that stores all available cases and classifies new cases based on a similarity measure
  - We allow K to vary to determine what value of K will produce the best classification performance – correctly identifying 2012 cohorts that were employed and those that realized stable employment
- The classification accuracy that depends on the number of correctly classified (true positives plus true negatives) individuals reaches about 0.65 with k equaling about 65

K Nearest Neighbor Classification Accuracy

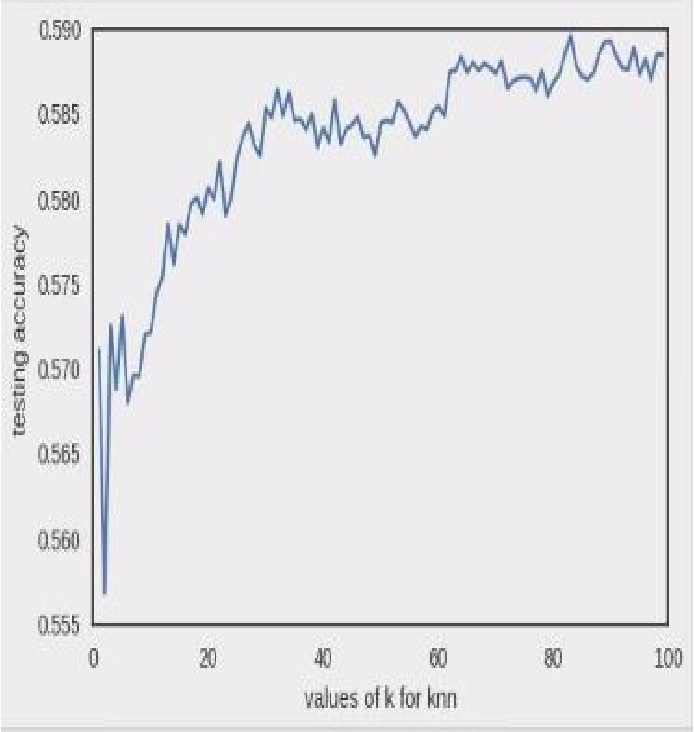
Employment

Accuracy less than 0.65



Stable Employment

Accuracy less than 0.59



Training and Testing Classification Models

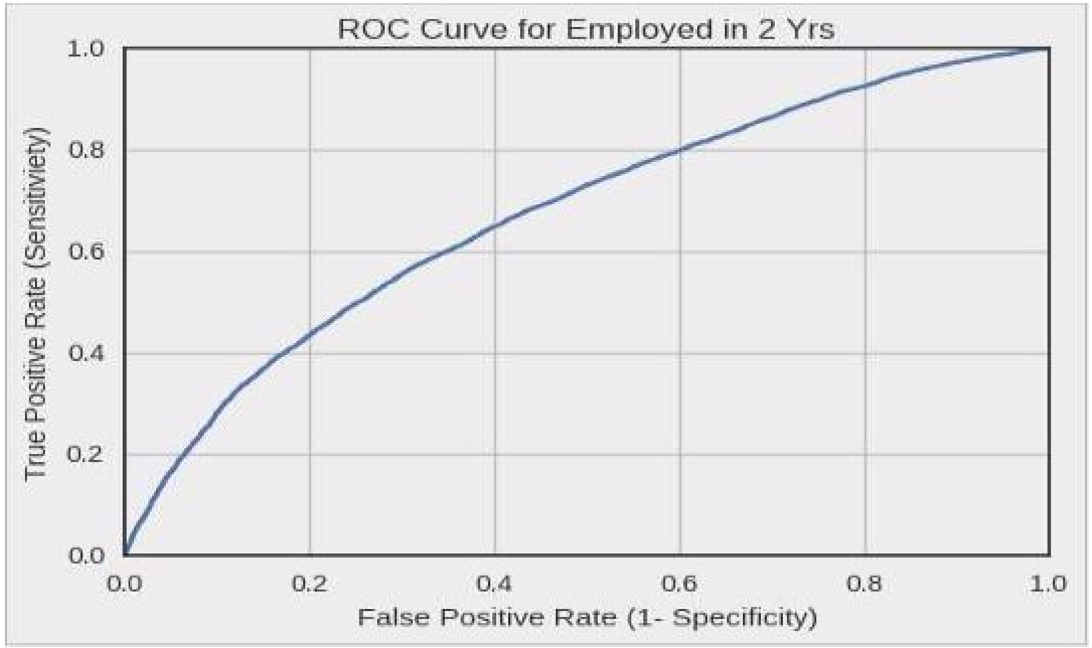
- Logistic Classification Model
  - A regression model where the dependent variable is categorical
  - Produced a higher classification accuracy, using the same features, on the test (2012 cohort) data of 0.67
  - Correctly classified 62% of the 2012 cohort as finding stable employment

Performance of Logistic Classification Model Null (100%) versus Classification Accuracies

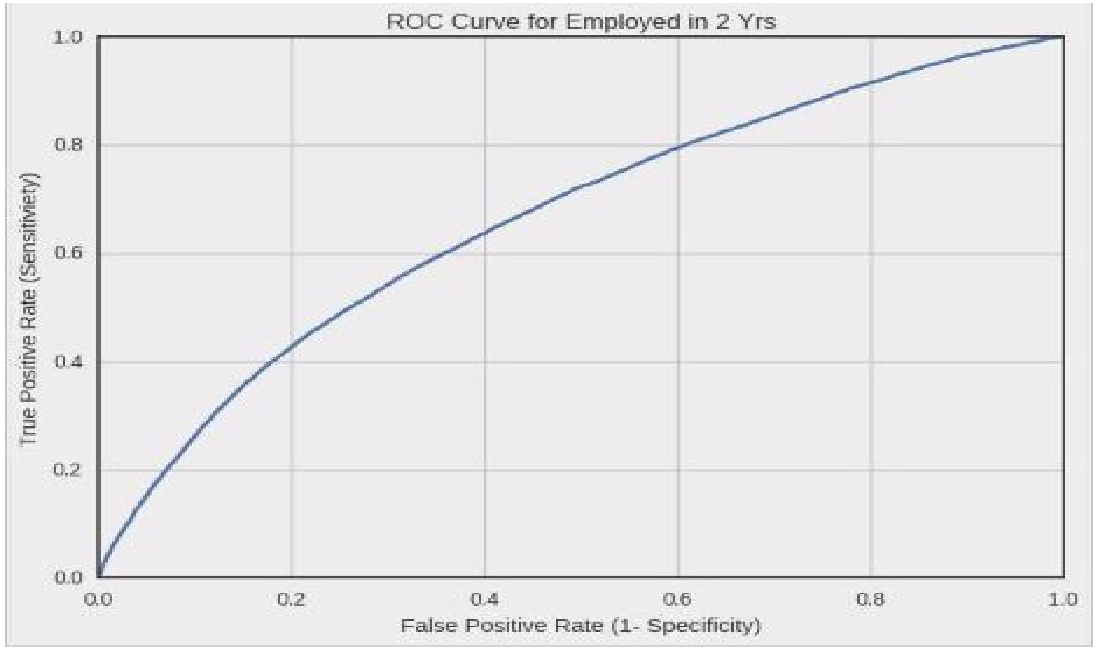
- Null Accuracy for employment of 2012 cohort
  - With a naïve approach, correctly classify 64% of the time
  - With Logistic model, correctly classify 67% of the time
- Null Accuracy for stable employment of 2012 Cohort
  - With a naïve approach, correctly classify 50% of the time
  - With Logistic model, correctly classify 62% of the time
- Area Under the ROC (receiver operating characteristic) curve
  - Maximize True Positive Rate (or Sensitivity)
  - Minimize False Positive Rate (or 1 – Specificity)

Performance of Logistic Classification Model

Employment



Stable Employment



Null Accuracy versus Classification Accuracy of Logistic Classification Model

- Employment within 8 quarters
    - 0.64 vs. 0.67
  - Lives in Cook county
    - 0.59 vs. 0.61
  - Lives outside Cook county
    - 0.68 vs. 0.71
- Stable Employment within 8 quarters
    - 0.50 vs. 0.62
  - Lives in Cook county
    - 0.43 vs. 0.63
  - Lives outside Cook county
    - 0.55 vs. 0.63

	Employed within 2 Years of Release		
	All	**Lived in Cook**	**Lived outside Cook**
Null Accuracy	0.64	0.59	0.68
Classification Accuracy	0.67	0.61	0.71
AUC (area under the curve)	0.67	0.63	0.70
	Realized Stable Employment within 2 Years		
	All	**Lived in Cook**	**Lived outside Cook**
Null Accuracy	0.50	0.43	0.55
Classification Accuracy	0.62	0.63	0.63
AUC (area under the curve)	0.66	0.63	0.67

When Model Performs Well

- True Positive Rate – Sensitivity or Recall
  - Entire population of those released: 0.90
  - Live in Cook county: 0.88
  - Live outside Cook County: 0.92
- True Negative Rate – Specificity
  - Entire population of those released: 0.72
  - Live in Cook county: 0.80
  - Live outside Cook County: 0.51
- Model does relatively well identifying those realizing employment within 2 years of release
- Model does relatively well at identifying those in Cook county that don't find stable employment

	Employed within 2 Years of Release		
	All	Lived in Cook	Lived outside Cook
True Positive Rate - TP/(TP + FN)	0.90	0.88	0.92
Specificity - TN/(TN + FP)	0.24	0.22	0.29
False Positive Rate	0.76	0.78	0.71
	Realized Stable Employment within 2 Years		
	All	Lived in Cook	Lived outside Cook
True Positive Rate - TP/(TP + FN)	0.59	0.37	0.73
Specificity - TN/(TN + FP)	0.66	0.80	0.51
False Positive Rate	0.34	0.20	0.49

Findings:
Modeling the impact of employment outcome predictors

Likelihood of employment within 2 years of release

- Personal characteristics
  - Whites are more than 2 times likely to be employed than others
  - The likelihood of employment for Blacks, women and those with kids is more modest, 10% to 14%
  - Formerly incarcerated with more than an elementary education and less than post-secondary education have the greatest likelihood of employment, 34%
    - Success on standardized reading tests increases the potential for employment, 6%
  - As age at time of release increases the employment probability decreases, 2% per year
    - Those in the lowest segment of jail time have an 18% greater chance for employment and those in the highest segment, 10% less chance of employment

Likelihood of employment within 2 years of release

- Value-Added human capital while incarcerated
  - Those who successfully complete the earned time towards a GED (60 days) are 35% more likely to be employed
  - The likelihood of employment for those who participate in the industrial training programs is 74% higher than those who do not
    - However, those who participate more than 2 years are nearly 60% less likely to find employment

- Local labor markets
  - Formerly incarcerated who resettle in Cook are nearly 20% more likely to find employment than others
  - Resettlement in Cook neighborhoods where jobs require less than a post-secondary degree typically decreases the chance of employment, 25% to 30%

Likelihood of employment within 2 years of release- Cook vs Non-Cook

- Personal characteristics
  - Race and gender impacts are more prominent in Non-Cook
  - Likelihood of employment due to education is similar across local geographies
    - Standardized reading scores only have a significant impact in Non-Cook
  - Age at release and jail time generated similar ratios in Cook and Non-Cook

- Value-Added human capital while incarcerated
  - Those who successfully complete the earned time towards a GED (60 days) are 30% to 35% more likely to be employed in Cook and Non-Cook
  - Participation in industrial training programs has no impact on employment outcomes in Cook
  - The likelihood of employment for those who participate in the industrial training programs is more than 2 times higher than those who do not among the formerly incarcerated who resettle in non-Cook
    - However, those who participate more than 2 years are more than 60% less likely to find employment

Likelihood of stable employment within 2 years of release- Overall

- Personal characteristics
  - Blacks are less likely to find stable employment
  - Other personal variables have a similar impact as reported for the likelihood of finding employment
- Value-Added human capital while incarcerated
  - Value-added HC variables have a similar impact as reported for the likelihood of finding employment
- Local labor market
  - Labor market variables have a similar impact as reported for the likelihood of finding employment

Likelihood of stable employment within 2 years of release- Cook vs Non-Cook

- Personal characteristics
  - Likelihood of establishing stable employment is similar to finding employment with one exception
    - Whites are no more likely to establish stable employment in Cook than others but more than 2 times more likely in non-Cook

- Value-Added human capital while incarcerated
  - In Cook, none of the value-added HC are significant for establishing stable employment
  - In non-Cook, earned credit towards a GED and participation in industrial training impact stable employment

Summary Findings

- Modeling the Classification of Employment Outcomes
  - Logistic regression produces a higher classification accuracy than k-nearest neighbor
  - Model classifying employment within 2 years produces better results for true positives than stable employment in both Cook and non-Cook
    - True negative rate higher in Cook than non-Cook
- Modeling the impact of employment outcome predictors
  - Employment within 2 years: major impacts
    - Personal characteristics: race and high school degree (or equivalent) at time of admission
    - Value-added HC: earned credit towards GED and industrial training (less than 2 years)
    - Local labor market: earned credit towards GED impacts in both Cook and non-Cook; industrial training (less than 2 years) impacts only non-Cook
  - Stable Employment within 2 years: major impacts
    - Similar pattern of impacts to finding employment although generally at lower odds ratios
    - Local labor market: earned credit towards GED impacts only non-Cook; industrial training (less than 2 years) impacts only non-Cook

Implication of Findings for Policy Imperative

- Facilitating reentry of formerly incarcerated to relieve labor shortages
  - Employment outcomes for the formerly incarcerated are more robust in non-Cook than Cook
  - Alignment of DOC reentry policy with labor shortages would need to recognize the local labor market dynamic of the formerly incarcerated
  - Reentry policy that targets labor shortages in the non-Cook region may have the greatest potential for success
- Impact of value-added human capital during incarceration
  - Persistent positive effect of earned credit towards GED and industrial training programs on employment outcomes in non-Cook
- Mobility of labor
  - Models of labor market mobility typically identify barriers that prevent optimum supply and demand
  - Prison reentry programs need to recognize destination of parolee as potential barrier to optimum supply and demand

Next Steps

- Augment the current analysis
  - Join employment outcomes for the formerly incarcerated to firm characteristics to inform the formulation of job placement strategies
    - Clustering of the formerly incarcerated by firm size, firm average earnings or firm structure
    - Explore linkages between specific DOC industrial training programs and industry of employment for the formerly incarcerated
  - Broaden the comparison between logistic regression and alternative classification models
  - Distinguish employment outcome impacts comparing self-reported human capital at time of admission to documented value-added human capital while incarcerated
- Expand employment outcome measures for the formerly incarcerated
  - patterns of hiring, separations, job stability with the same employer, earnings in stable jobs, and a longitudinal perspective on job flows across industries

Appendix

Methodology: Labor Market Features

- Personal characteristics
  - Race: racewh (1= whites, 0= others); racebl (1= blacks, 0= others)
  - Gender (1= male, 0= female)
  - Kids (0 to 6 kids)
    - Top coded at 6 kids
  - Education at admission
    - Educ (1= none; 2= elementary; 3= some HS; 4= HS degree; 5= some post-secondary technical; 6= some post-secondary non-technical)
    - Educ Elem (1= none or some elementary; 0= other)
    - Educ Post-Sec (1= at least some post-secondary; 0= other)
  - TABE math (standardized math score reported at admission)
  - TABE reading (standardized reading score reported at admission)
  - Age at release (in years)
  - Jail time (in days)

Methodology: Labor Market Features

- Value-added human capital during incarceration
  - Earned time credit for education (number of days credited for education program)
  - Earned time credit for obtaining GED (number of days credited for GED pursuit)
  - Industrial training programs (see list of training programs)
    - Participatie Ind Train (1= 1 month or more participation; 0= 0 months participation)
    - Participation Ind Train 75% (1= 24 months or more of participation; 0= less than 24 months)

- Local Labor Markets
  - Cook vs Non-Cook
    - Intended destination address of parolee as either in Cook county or non-Cook county in Illinois
  - Education composition of jobs by Cook neighborhood
    - Cook neigh < HS (1= two neighborhoods with the highest percentage of employed persons with less than High School
    - Cook neigh HS (1= two neighborhoods with the highest percentage of employed persons with High School degree or equivalent
    - Cook neigh Post-Sec (1= two neighborhoods with the highest percentage of employed persons with some Post-Secondary
    - Cook neigh Post-Sec degree (1= two neighborhoods with the highest percentage of employed persons with a Post-Secondary degree

DOC Industrial Training Programs

Administration		Mattresses
Animal Grooming		Meat Processing
Bakery		Metal Furniture
Boxes		Milk/Juice Proc.
Broom & Wax		Optical
C.E.O		Planning
Distribution		Recycling
Engraving/Call Cntr.		Refinishing
Farm Administration		Sewing
Fiscal		Sign Shop
Furniture		Soap Shop
Garment		Stores
Helping Paws		Trades
Knit Shop		Trucking
Laundry		Vehicles/Fuel
Marketing		Waste Disposal

Training Set: Descriptive Statistics(*)				
		Total	Cook	Non-Cook
worked in 2 years				
	no	10,103	4,972	5,131
	yes	18,162	7,621	10,541
worked 3 consecutive quarters				
	no	14,171	6,951	7,220
	yes	14,094	5,642	8,452
racewh				
	no	20,053	11,316	8,737
	yes	8,212	1,277	6,935
racebl				
	no	11,804	2,814	8,990
	yes	16,461	9,779	6,682
gender				
	female	2,350	959	1,391
	male	25,915	11,634	14,281
kids (mean)		1.58	1.67	1.51
age at release (mean)		33.78	33.89	33.69
number of days jail (mean)		176.11	195.56	160.49
credit earned				
	education (mean)	8.21	6.49	9.59
	GED (mean)	1.79	1.27	2.22
tabe math (mean)		1.81	1.53	2.04
tabe reading (mean)		2.21	1.87	2.48
education				
	elementary or less	1,871	641	1,230
	some high school	12,164	6,023	6,142
	high school degree or equivalent	11,017	4,480	6,537
	some post-secondary technical	180	93	87
	some post-secondary non-technical	3,033	1,357	1,676
DOC industrial training				
	no	28,005	12,485	15,520
	yes	260	108	152
DOC industrial training				
	other	28,197	12,560	15,637
	highest quartile	68	33	35

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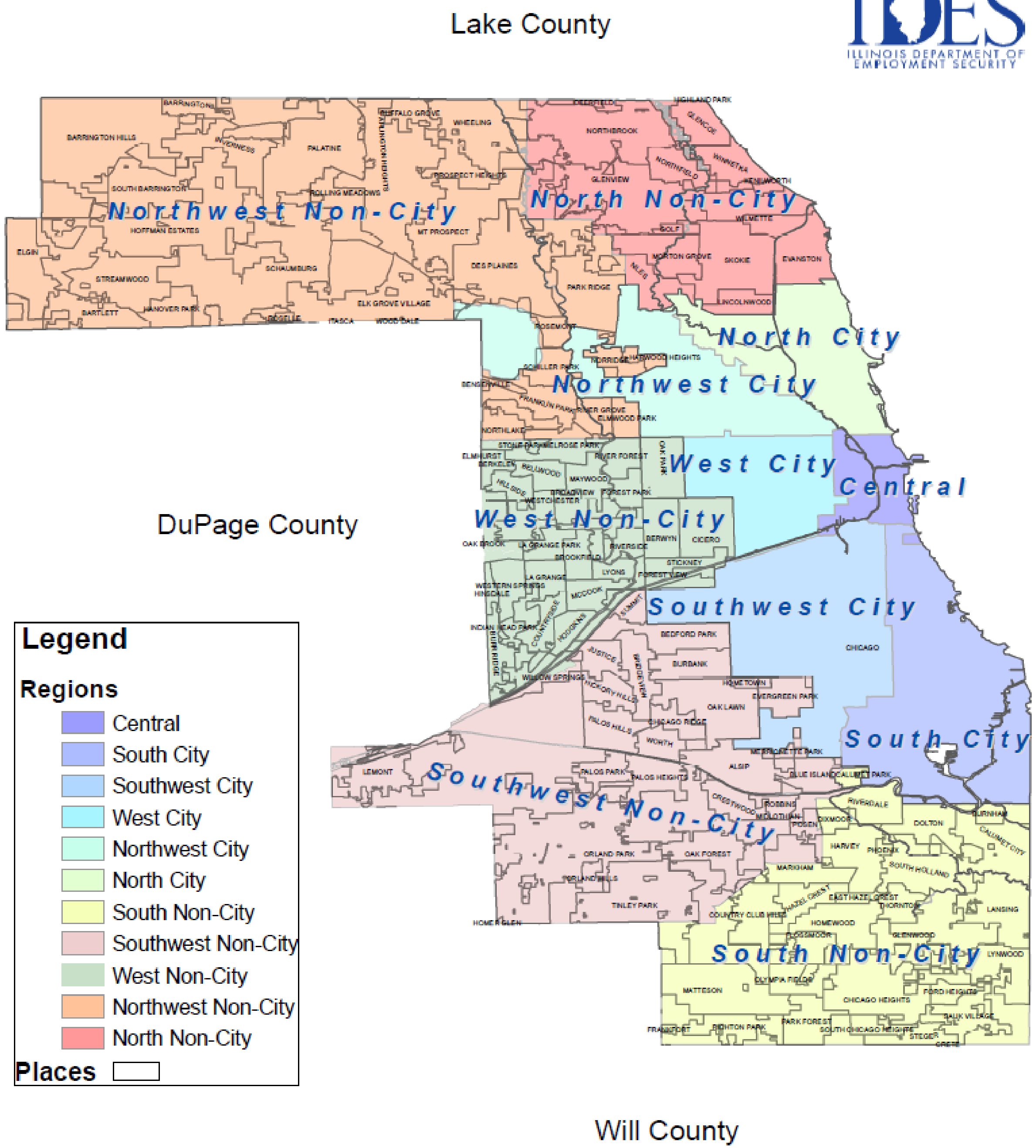

Worked in 2 Years: Total

```
Logit Regression Results
==============================================================================
Dep. Variable:           worked_n_2yrs   No. Observations:                28265
Model:                           Logit   Df Residuals:                    28244
Method:                            MLE   Df Model:                           20
Date:                 Sat, 03 Jun 2017   Pseudo R-squ.:                 0.06995
Time:                         08:35:06   Log-Likelihood:                -17138.
converged:                        True   LL-Null:                       -18427.
                                         LLR p-value:                     0.000
===========================================================================================
                              coef    std err          z      P>|z|      [95.0% Conf. Int.]
-------------------------------------------------------------------------------------------
racervwh                    0.8200      0.044     18.554      0.000         0.733     0.907
racervbl                    0.1295      0.039      3.347      0.001         0.054     0.205
sex                        -0.1508      0.042     -3.592      0.000        -0.233    -0.069
kidsrv                      0.0903      0.008     10.724      0.000         0.074     0.107
agerlse                    -0.0207      0.001    -16.269      0.000        -0.023    -0.018
jailtime                   -0.0006   8.17e-05     -6.792      0.000        -0.001    -0.000
jailtime1                   0.1652      0.034      4.911      0.000         0.099     0.231
jailtime2                  -0.0952      0.040     -2.354      0.019        -0.174    -0.016
gttyp17                    -0.0003      0.000     -0.597      0.551        -0.001     0.001
gttyp24                     0.0060      0.001      3.993      0.000         0.003     0.009
tabe1mthsrv2               -0.0174      0.013     -1.304      0.192        -0.044     0.009
tabe1rdgsrv2                0.0552      0.011      5.036      0.000         0.034     0.077
educlvlrv                   0.2914      0.014     21.506      0.000         0.265     0.318
educlvlrv2                 -0.4531      0.054     -8.323      0.000        -0.560    -0.346
educlvlrv4                 -0.7367      0.096     -7.679      0.000        -0.925    -0.549
duration_months_calcrv3     0.5543      0.181      3.056      0.002         0.199     0.910
duration_months_calcrv5    -0.8502      0.316     -2.691      0.007        -1.469    -0.231
c000rv1                     0.1780      0.041      4.313      0.000         0.097     0.259
cd01rv2                    -0.2968      0.050     -5.907      0.000        -0.395    -0.198
cd02rv2                    -0.0105      0.047     -0.223      0.823        -0.103     0.082
cd03rv2                    -0.3184      0.055     -5.806      0.000        -0.426    -0.211
```

Worked in 2 Years: Cook

```
Logit Regression Results
==============================================================================
Dep. Variable:          worked_n_2yrs   No. Observations:                12593
Model:                          Logit   Df Residuals:                    12576
Method:                           MLE   Df Model:                           16
Date:                Sat, 03 Jun 2017   Pseudo R-squ.:                 0.04332
Time:                        08:39:23   Log-Likelihood:                -8082.1
converged:                       True   LL-Null:                       -8448.1
                                        LLR p-value:                 2.054e-145
=============================================================================================
                              coef    std err          z      P>|z|      [95.0% Conf. Int.]
---------------------------------------------------------------------------------------------
racervwh                    0.2769      0.087      3.189      0.001         0.107     0.447
racervbl                   -0.5353      0.056     -9.573      0.000        -0.645    -0.426
sex                        -0.0294      0.061     -0.484      0.629        -0.149     0.090
kidsrv                      0.0728      0.012      6.180      0.000         0.050     0.096
agerlse                    -0.0104      0.002     -5.622      0.000        -0.014    -0.007
jailtime                   -0.0003      0.000     -3.011      0.003        -0.001    -0.000
jailtime1                   0.1056      0.050      2.114      0.035         0.008     0.203
jailtime2                  -0.0764      0.054     -1.407      0.159        -0.183     0.030
gttyp17                     0.0006      0.001      0.672      0.502        -0.001     0.002
gttyp24                     0.0063      0.002      2.557      0.011         0.001     0.011
tabe1mthsrv2                0.0095      0.020      0.467      0.640        -0.030     0.049
tabe1rdgsrv2                0.0288      0.017      1.744      0.081        -0.004     0.061
educlvlrv                   0.3055      0.020     15.621      0.000         0.267     0.344
educlvlrv2                 -0.4246      0.088     -4.798      0.000        -0.598    -0.251
educlvlrv4                 -0.5996      0.130     -4.618      0.000        -0.854    -0.345
duration_months_calcrv3     0.2739      0.256      1.071      0.284        -0.227     0.775
duration_months_calcrv5    -0.5791      0.442     -1.309      0.191        -1.446     0.288
=============================================================================================
```

Worked in 2 Years: non-Cook

```
Logit Regression Results
==============================================================================
Dep. Variable:          worked_n_2yrs   No. Observations:                15672
Model:                          Logit   Df Residuals:                    15655
Method:                           MLE   Df Model:                           16
Date:                Mon, 05 Jun 2017   Pseudo R-squ.:                 0.09842
Time:                        13:13:45   Log-Likelihood:                -8934.4
converged:                       True   LL-Null:                       -9909.7
                                        LLR p-value:                     0.000
=============================================================================================
                             coef    std err          z      P>|z|      [95.0% Conf. Int.]
---------------------------------------------------------------------------------------------
racervwh                   1.1744      0.055     21.339      0.000         1.067     1.282
racervbl                   0.5812      0.052     11.099      0.000         0.479     0.684
sex                       -0.2236      0.058     -3.834      0.000        -0.338    -0.109
kidsrv                     0.1012      0.012      8.331      0.000         0.077     0.125
agerlse                   -0.0277      0.002    -15.630      0.000        -0.031    -0.024
jailtime                  -0.0009      0.000     -7.235      0.000        -0.001    -0.001
jailtime1                  0.1774      0.046      3.846      0.000         0.087     0.268
jailtime2                 -0.0832      0.060     -1.379      0.168        -0.201     0.035
gttyp17                   -0.0005      0.001     -0.815      0.415        -0.002     0.001
gttyp24                    0.0048      0.002      2.552      0.011         0.001     0.009
tabe1mthsrv2              -0.0243      0.018     -1.352      0.176        -0.060     0.011
tabe1rdgsrv2               0.0646      0.015      4.352      0.000         0.035     0.094
educlvlrv                  0.2886      0.019     15.350      0.000         0.252     0.325
educlvlrv2                -0.4088      0.071     -5.769      0.000        -0.548    -0.270
educlvlrv4                -0.8734      0.145     -6.027      0.000        -1.157    -0.589
duration_months_calcrv3    0.7823      0.264      2.958      0.003         0.264     1.301
duration_months_calcrv5   -1.0810      0.456     -2.369      0.018        -1.975    -0.187
=============================================================================================
```

Stable Employment: Total

Logit Regression Results

Dep. Variable:	worked_3qtrs	No. Observations:	28265
Model:	Logit	Df Residuals:	28244
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converged:	True	LL-Null:	-19592.
		LLR p-value:	0.000

	coef	std err	z	P>|z|	[95.0% Conf.	Int.]
racervwh	0.4704	0.042	11.318	0.000	0.389	0.552
racervbl	-0.1189	0.038	-3.138	0.002	-0.193	-0.045
sex	-0.2912	0.039	-7.465	0.000	-0.368	-0.215
kidsrv	0.0653	0.008	8.136	0.000	0.050	0.081
agerlse	-0.0215	0.001	-17.338	0.000	-0.024	-0.019
jailtime	-0.0005	8.63e-05	-5.445	0.000	-0.001	-0.000
jailtime1	0.1343	0.031	4.286	0.000	0.073	0.196
jailtime2	-0.1278	0.040	-3.166	0.002	-0.207	-0.049
gttyp17	0.0003	0.000	0.738	0.461	-0.001	0.001
gttyp24	0.0043	0.001	3.262	0.001	0.002	0.007
tabe1mthsrv2	0.0040	0.012	0.333	0.739	-0.020	0.028
tabe1rdgsrv2	0.0300	0.010	3.035	0.002	0.011	0.049
educlvlrv	0.2496	0.012	19.970	0.000	0.225	0.274
educlvlrv2	-0.4547	0.056	-8.076	0.000	-0.565	-0.344
educlvlrv4	-0.6657	0.104	-6.413	0.000	-0.869	-0.462
duration_months_calcrv3	0.5136	0.158	3.255	0.001	0.204	0.823
duration_months_calcrv5	-0.6912	0.306	-2.259	0.024	-1.291	-0.091
c000rv1	0.1100	0.039	2.838	0.005	0.034	0.186
cd01rv2	-0.3339	0.048	-6.887	0.000	-0.429	-0.239
cd02rv2	0.0134	0.047	0.287	0.774	-0.078	0.105
cd03rv2	-0.3776	0.053	-7.102	0.000	-0.482	-0.273

Stable Employment: Cook

```
Logit Regression Results
==============================================================================
Dep. Variable:           worked_3qtrs   No. Observations:                12593
Model:                          Logit   Df Residuals:                    12576
Method:                           MLE   Df Model:                           16
Date:                Sat, 03 Jun 2017   Pseudo R-squ.:                 0.03881
Time:                        08:49:36   Log-Likelihood:                -8324.5
converged:                       True   LL-Null:                       -8660.6
                                        LLR p-value:                 1.010e-132
==========================================================================================
                             coef    std err          z      P>|z|      [95.0% Conf. Int.]
------------------------------------------------------------------------------------------
racervwh                  -0.0423      0.078     -0.540      0.589        -0.196     0.111
racervbl                  -0.7107      0.053    -13.323      0.000        -0.815    -0.606
sex                       -0.2271      0.058     -3.902      0.000        -0.341    -0.113
kidsrv                     0.0489      0.011      4.253      0.000         0.026     0.071
agerlse                   -0.0137      0.002     -7.497      0.000        -0.017    -0.010
jailtime                  -0.0002      0.000     -2.118      0.034        -0.000 -1.67e-05
jailtime1                  0.0258      0.048      0.536      0.592        -0.068     0.120
jailtime2                 -0.1505      0.055     -2.750      0.006        -0.258    -0.043
gttyp17                    0.0003      0.001      0.400      0.689        -0.001     0.002
gttyp24                    0.0042      0.002      1.892      0.059        -0.000     0.009
tabe1mthsrv2               0.0214      0.019      1.132      0.258        -0.016     0.059
tabe1rdgsrv2               0.0134      0.015      0.868      0.385        -0.017     0.044
educlvlrv                  0.2695      0.018     14.728      0.000         0.234     0.305
educlvlrv2                -0.3915      0.094     -4.184      0.000        -0.575    -0.208
educlvlrv4                -0.4669      0.138     -3.373      0.001        -0.738    -0.196
duration_months_calcrv3    0.2317      0.238      0.973      0.331        -0.235     0.699
duration_months_calcrv5   -0.5178      0.447     -1.158      0.247        -1.394     0.358
==========================================================================================
```

Stable Employment: non-Cook

Logit Regression Results

Dep. Variable:	worked_3qtrs	No. Observations:	15672
Model:	Logit	Df Residuals:	15655
Method:	MLE	Df Model:	16
Date:	Sat, 03 Jun 2017	Pseudo R-squ.:	0.07324
Time:	08:52:42	Log-Likelihood:	-10022.
converged:	True	LL-Null:	-10815.
		LLR p-value:	0.000

	coef	std err	z	P>|z|	[95.0% Conf. Int.]	
racervwh	0.7848	0.053	14.869	0.000	0.681	0.888
racervbl	0.2451	0.052	4.751	0.000	0.144	0.346
sex	-0.3453	0.053	-6.551	0.000	-0.449	-0.242
kidsrv	0.0720	0.011	6.386	0.000	0.050	0.094
agerlse	-0.0262	0.002	-15.546	0.000	-0.029	-0.023
jailtime	-0.0008	0.000	-6.134	0.000	-0.001	-0.001
jailtime1	0.1770	0.042	4.221	0.000	0.095	0.259
jailtime2	-0.0809	0.059	-1.367	0.172	-0.197	0.035
gttyp17	0.0005	0.001	0.935	0.350	-0.001	0.002
gttyp24	0.0035	0.002	2.154	0.031	0.000	0.007
tabe1mthsrv2	0.0018	0.016	0.114	0.909	-0.029	0.033
tabe1rdgsrv2	0.0336	0.013	2.592	0.010	0.008	0.059
educlvlrv	0.2304	0.017	13.545	0.000	0.197	0.264
educlvlrv2	-0.4617	0.072	-6.453	0.000	-0.602	-0.321
educlvlrv4	-0.8900	0.159	-5.593	0.000	-1.202	-0.578
duration_months_calcrv3	0.6994	0.217	3.228	0.001	0.275	1.124
duration_months_calcrv5	-0.7765	0.427	-1.819	0.069	-1.613	0.060

Logistics Regression Results: Odds Ratios							
		Worked In 2 Years					
		Total		Cook		Non-Cook	
		odds ratio	sig	odds ratio	sig	odds ratio	sig
Personal							
	Racewh	2.271	0.001	1.319	0.001	3.236	0.001
	Racebl	1.138	0.001	0.586	0.001	1.788	0.001
	Gender	0.860	0.001	0.097		0.800	0.001
	Kids	1.095	0.001	1.076	0.001	1.106	0.001
	educ level	1.338	0.001	1.357	0.001	1.335	0.001
	educ (elem)	0.636	0.001	0.654	0.001	0.664	0.001
	educ (post-sec)	0.479	0.001	0.549	0.001	0.418	0.001
	tabe math	0.983		1.010		0.976	
	tabe reading	1.057	0.001	1.029		1.067	0.001
	age release	0.980	0.001	0.990	0.001	0.973	0.001
	jailtime	0.999	0.001	1.000	0.010	0.999	0.001
	jailtime (25%)	1.180	0.001	1.111	0.050	1.194	0.001
	jailtime (75%)	0.909	0.050	0.927		0.920	
Value-Added Human Capital							
	earned time ed	1.000		1.001		1.000	
	earned time GED	1.006	0.001	1.006	0.050	1.005	0.050
	Participate Ind Train	1.741	0.010	1.315		2.187	0.010
	Participate Ind Train (75%)	0.427	0.010	0.560		0.339	0.050
Local Labor Markets							
	Cook vs NonCook	1.195	0.001				
	Cook neigh (< HS)	0.743	0.001				
	Cook neigh (HS)	0.990					
	Cook neigh (post-sec)	0.727	0.001				

Logistics Regression Results: Odds Ratios							
		Stable Employment					
		Total		Cook		Non-Cook	
		odds ratio	sig	odds ratio	sig	odds ratio	sig
Personal							
	Racewh	1.601	0.001	0.959		2.192	0.001
	Racebl	0.888	0.010	0.491	0.001	1.278	0.001
	Gender	0.747	0.001	0.797	0.001	0.708	0.001
	Kids	1.067	0.001	1.050	0.001	1.075	0.001
	educ level	1.284	0.001	1.309	0.001	1.259	0.001
	educ (elem)	0.635	0.001	0.676	0.001	0.630	0.001
	educ (post-sec)	0.514	0.001	0.627	0.001	0.411	0.001
	tabe math	1.004		1.022		1.002	
	tabe reading	1.030	0.010	1.014		1.034	0.010
	age release	0.979	0.001	0.986	0.001	0.974	0.001
	jailtime	1.000	0.001	1.000	0.050	0.999	0.001
	jailtime (25%)	1.144	0.001	1.026		1.194	0.001
	jailtime (75%)	0.880	0.010	0.860	0.010	0.922	
Value-Added Human Capital							
	earned time ed	1.000		1.000		1.001	
	earned time GED	1.004	0.001	1.004		1.004	0.050
	Participate Ind Train	1.671	0.001	1.261		2.013	0.001
	Participate Ind Train (75%)	0.501	0.050	0.596		0.460	
Local Labor Markets							
	Cook vs NonCook	1.116	0.010				
	Cook neigh (< HS)	0.716	0.001				
	Cook neigh (HS)	1.013					
	Cook neigh (post-sec)	0.686	0.001				