

Ex-offender  
employment:

Intervening to  
increase likelihood  
of stable  
employment post-  
prison

# Team 6:



Ewa Gallagher  
Illinois Department of Employment  
Security



Julie Steenson  
City of Kansas City, Missouri



Gene Leynes  
City of Chicago, IL

Edward Torufa  
Missouri Department of Economic  
Development

Why  
this  
project  
?

Data Access

- Illinois Department of Corrections
- Illinois wage
- Missouri wage

Who is  
our  
focus?

Ex-offender ability to earn  
wages built on previous  
class work

- What factors are predictive of a person's ability to earn wages post-release from prison
- Classified patterns of employment to evaluate stable employment

We got  
curious  
?

What impact does living on  
a state line have?

- Would Illinois ex-offenders seek work in Missouri, especially in the Missouri border counties near St. Louis.

# Literature Review

## *Employment after Prison: A longitudinal study of releasees in three states.*

**- Visher, Debus and Yahner**

**Findings:** Prisoners with work experience before or in prison, higher levels of family interaction, lower Substance Abuse, pre-release employment linkages - had higher employment after release. Within eight months of release, 65% of prisoners had found employment at some point and **45% were currently employed at the eight-month mark.**

*“One important finding of the analyses in this report was the particular vulnerability of those without previous work experiences. Prison administrators and service providers must realize that individuals with weak employment and educational histories will need additional assistance with finding a job after prison”*

<http://cw.routledge.com/textbooks/9780415884433/instructorManual/data/Visher,%20Debus-Sherrill,%20Yahner%20-%20Employment%20after%20prison.pdf>

- This study was done by pre-release and post-release interviews with 740 former male prisoners in Illinois, Ohio and Texas. Wage records were not available as a validation of the former prisoners self-reporting. Our work hopes to build on this study.

# Literature Review

## Post-Release Employment of the formerly incarcerated: labor market perspective

Darnell Cloud, Jill Coughlin, Noa Kay, Tanya Hannah and George Putnam

### Findings:

- Model classifying employment within two years produces better results for true positives than stable employment in both Cook and non-Cook
- Modeling impact of employment outcomes predictors:
  - Employment within 2 years: major impacts
    - Value-added HC: earned credit towards GED and industrial training (less than 2 years)
    - Local labor market: earned credit towards GED impacts both Cook and non-Cook; industrial training (less than 2 years) impacts only 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

Modeling outcomes: logistic regression produces a higher classification accuracy than k-nearest neighbor

# Key Policy Implication

- **KEY POLICY IMPLICATIONS:**

- From lit review: ex-offenders who are employed a year out are less likely to be re-incarcerated (we did not look at re-incarceration as part of our study).

## **POTENTIAL INTERVENTIONS:**

- Provide and target employment programs for individuals most at risk for prison.
- Provide in-prison work programs that mimic pre-prison employment

# Our Research Question and Data Sources

- **Descriptive Analysis:** What proportion of ex-offenders obtain steady wages/stable employment (defined as wages earned in consecutive three quarters) post-release?
- **Predictive Analysis:** What factors influence whether Illinois ex-offenders find work after release in either Illinois or Missouri?
- **Data Sources:**
  - Illinois Department of Corrections, prison exit table 2010 - 2013
  - Illinois Department of Employment Security (IDES), wages earned 2005-2015
  - Missouri Division of Employment Security ( MoDOR), wages earned 2005-2015

# Assumptions and Barriers

## Assumptions

- Records for Exit data are complete and can be joined to data tables for wages in both states
- Ex-offenders will seek work, primarily in minimum wage level jobs
- We limited ex-offenders from Illinois who would seek employment in Missouri to counties near the border only

## Barriers

- We had originally wanted to assess the impact of parole time on wages, but it appears that the parole data we have does not have enough records to help us answer our questions.
- Department of Corrections data is mostly complete, but lacks some details consistently enough to be valuable (job training while in prison for instance). Thus, all variables that could impact post-release employment were not taken into consideration.
- Very important note: We did account for multiple entries into the system!



# Analysis Process

- **Step One:** Join Admin and Exit tables from the Illinois Department of Correction to Wages tables from Illinois Department Employment Security and Missouri Department of Labor for time period between 2006-2015.
- **Step Two:** Identify descriptive characteristics of incarcerated that influence an ex-offender's ability to earn wages post-prison.
- **Step Three:** Evaluate the performance of alternative models to classify employment outcomes of the recently incarcerated.

# Describing the data

- In total, there were 103,496 records for Illinois ex-offenders in our sample:
  - 44,800 or 43.29% earned wages (three quarters or more) post-release
  - An additional 1,336 or 1.29% of Illinois ex-offenders earned wages in Missouri counties close to the border\*
  - Total = 46,136 or 44.58%, very close to the study by Visser, Debus and Yahner
- However only 23,478 ex-offenders in Illinois and 553 in Missouri had **stable employment** (3 consecutive quarters of employment), which is a total of **23.22%**
- FINDING: most ex-offenders in Illinois tend to earn wages only in Illinois post-release

Number of quarters (We developed a schema that identified and aggregated individuals into nine separate “patterns”)	% of IL ex-offenders earning wages in IL	% of IL ex-offenders earning wages in MO
No wages earned in any quarters (00)	56.71	98.71
Wages earned in all eight quarters post-release (01)	10.45	0.14
Earned wages in 1 Qtr (02)	1.59	0.02
Earned wages in 2 Qtrs (03)	0.92	0.02
Earned wages in 3 Qtrs (04)	0.89	0.04
Earned wages in 4 Qtrs (05)	9.62	0.42
Earned wages in 5 Qtrs (06)	7.49	0.28
Earned wages in 6 Qtrs (07)	3.67	0.11
Earned wages in 7 Qtrs (08)	1.9	0.06
Other	6.78	0.19

\*Adams, Alexander, Calhoun, Jersey, Jackson, Madison Monroe, Randolph, St. Claire, Union

# Industries where ex-offenders were employed

---

Construction

---

Manufacturing

---

Wholesale and Retail Trade

---

Transportation and Warehousing

---

Professional, Scientific and Technical Services

---

Administrative and Support and Waste Management and Remediation Services (ex. Janitorial Services, Pest control, Landscaping, Temp services)

---

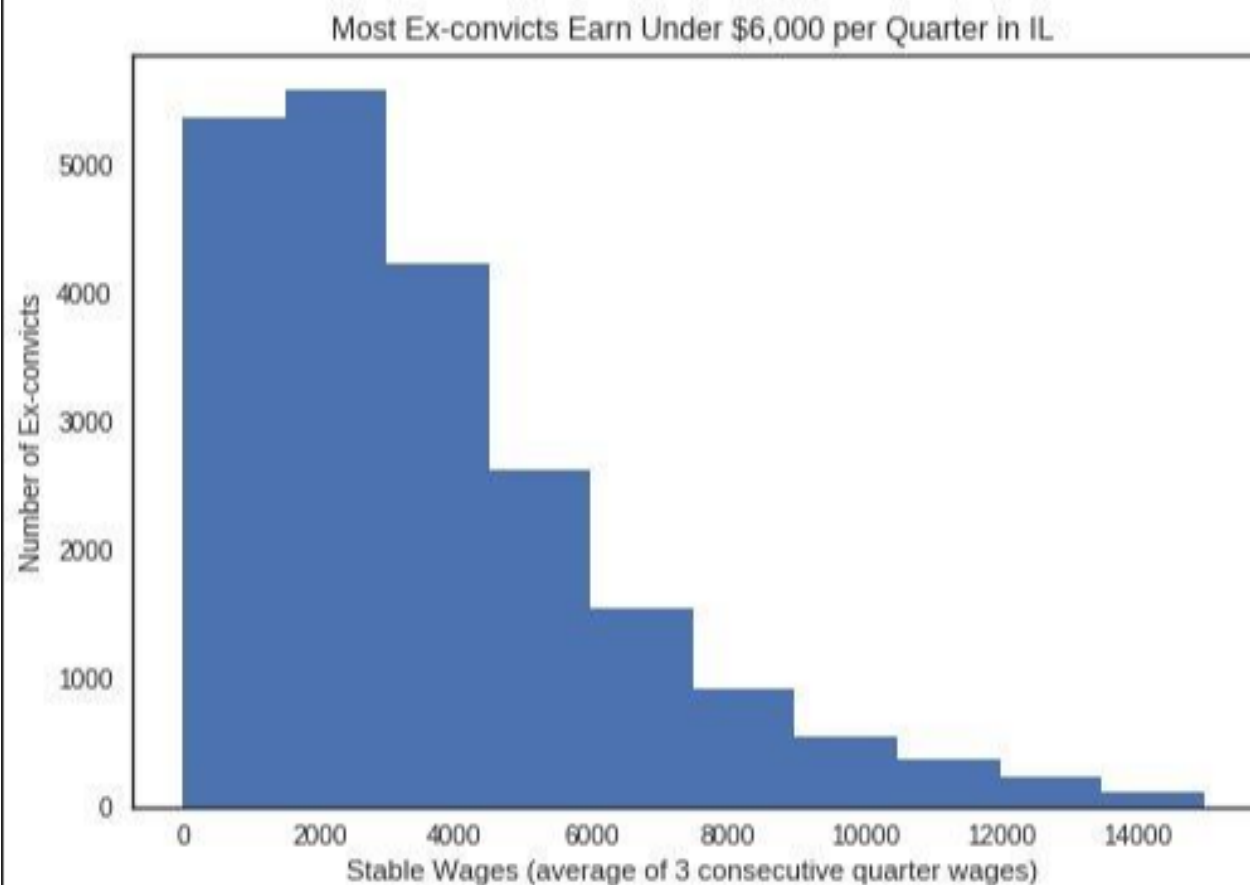
Accommodation and Food Services

*Previous research showed concentration in the following: construction, maintenance, cleaning, automotive, and food service.*

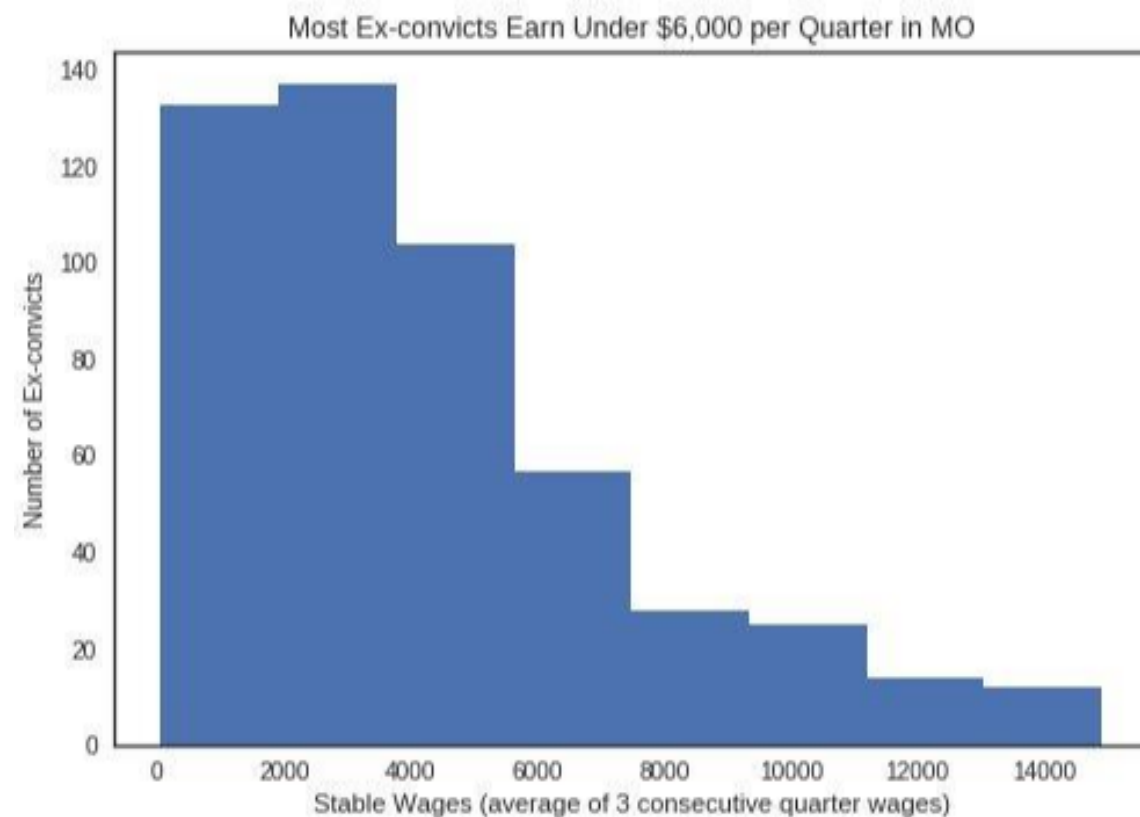
- Visher, Debus and Yahner

# Describing the data: wages earned in Illinois and Missouri

**Learning moment! We had to reduce the number of bins for MO because too few observations in more than 8 bins.**



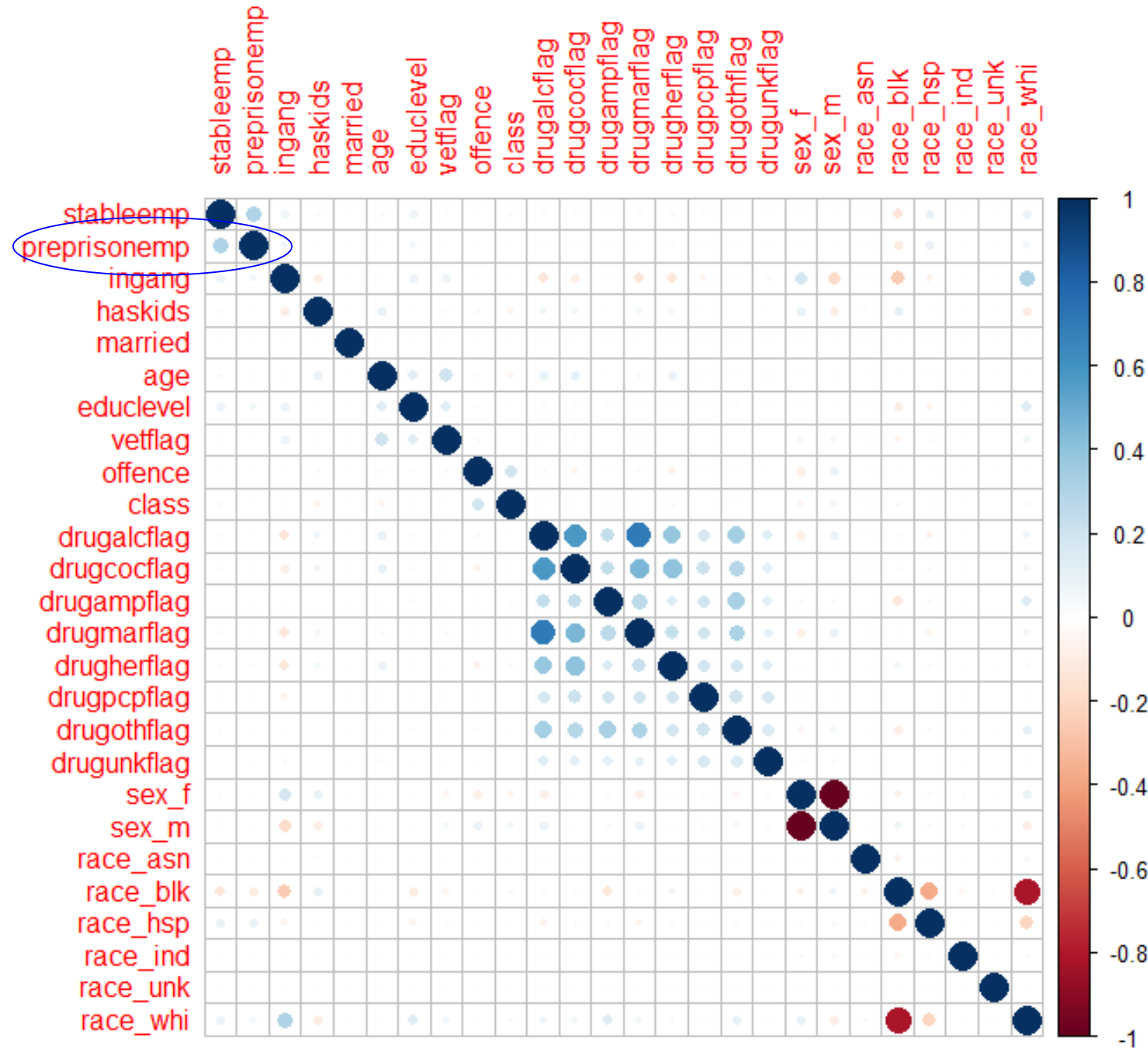
Source: IL IDES & IDOC



Source: MO\_DES & IDOC

# Correlation Factors

- **Positive Correlations for stable employment (y):**
  - “Preprisonemp”: Pre-prison wages earned in any of the four quarters prior to imprisonment
  - Race = Hispanic
- **Negative correlations:**
  - Race = black
- **Weak to no correlation:**
  - In a gang
  - Family situation: marital status, have kids
  - Age
  - Veteran status
  - Education level
  - Drug offenses by type



# Modeling for Illinois ex- offenders, with wages in Illinois:

We created a machine learning model that was:

- supervised,
- for classification,
- with a discrete target variable (employed or not)
- specifically predicting if that target variable would be true or not in the future.
- Using following features (cleaned and transformed): pre-prison employment, sex F, race (BLK, WHI, HSP), in gang, has kids, married, age, education, offence type, offence class, veteran, drug use

# Model of Illinois ex-offender's stable employment after release from prison:

- Split into train and test set

	Illinois
Test	34,150
Train	69,334

- Findings from Generalized Linear Model:

Change in pre-prison employment has a 40% effect on stable employment, if all other features are held constant.

# Regression model with stable employment as independent variable for Illinois:

## Generalized Linear Model Regression Results

```
=====
Dep. Variable:          stableemp      No. Observations:          69334
Model:                  GLM           Df Residuals:              69315
Model Family:          Gaussian       Df Model:                  18
Link Function:         identity       Scale:                    0.154223385984
Method:                IRLS          Log-Likelihood:           -33566.
Date:                  Fri, 22 Jun 2018 Deviance:                  10690.
Time:                  19:05:55       Pearson chi2:             1.07e+04
No. Iterations:        2
=====
```

	coef	std err	z	P> z	[0.025	0.975]
preprisonemp	0.4023	0.005	79.366	0.000	0.392	0.412
sex_F	0.0031	0.005	0.568	0.570	-0.008	0.014
race_BLK	0.2045	0.007	31.125	0.000	0.192	0.217
race_WHI	0.2626	0.007	36.583	0.000	0.249	0.277
race_HSP	0.3347	0.008	42.070	0.000	0.319	0.350
ingang	0.0359	0.003	10.650	0.000	0.029	0.043
haskids	0.0107	0.003	3.238	0.001	0.004	0.017
married	0.0266	0.077	0.345	0.730	-0.124	0.178
age	-0.0033	0.000	-22.512	0.000	-0.004	-0.003
educlevel	0.0615	0.003	20.061	0.000	0.055	0.067
offence	-0.0175	0.003	-5.172	0.000	-0.024	-0.011
class	0.0320	0.003	10.143	0.000	0.026	0.038
vetflag	-0.0321	0.012	-2.727	0.006	-0.055	-0.009
drugalcflag	0.0072	0.006	1.253	0.210	-0.004	0.018
drugcocflag	0.0097	0.007	1.411	0.158	-0.004	0.023
drugampflag	-0.0358	0.012	-2.900	0.004	-0.060	-0.012
drugmarflag	-0.0170	0.007	-2.592	0.010	-0.030	-0.004
drugherflag	0.0081	0.009	0.953	0.341	-0.009	0.025
drugpcpflag	0.0154	0.017	0.918	0.359	-0.018	0.048

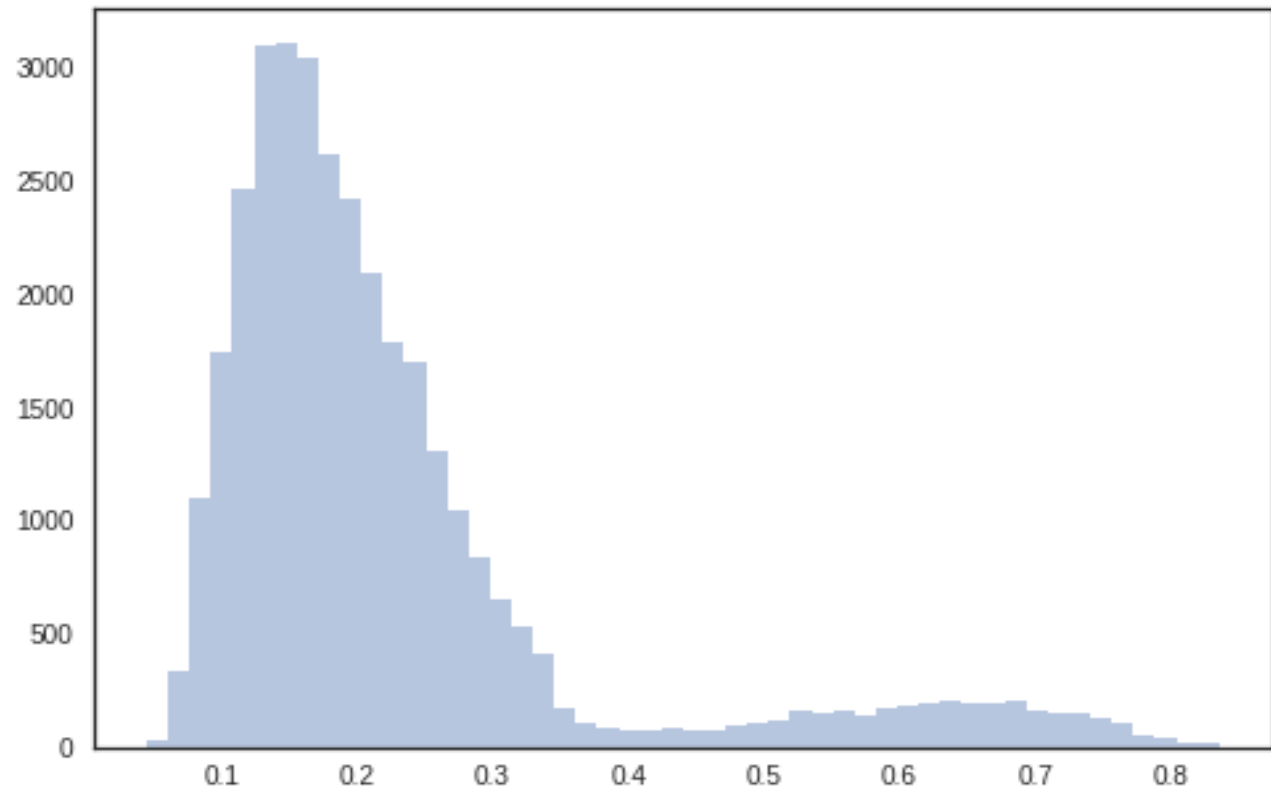
## Conclusions from regression (in layman's terms):

- Pre-prison employment is a significant factor with a 40% effect on stable employment
- Race is a factor
- Education level is significant



# Histogram of predicted values

Probability of stable employment is rather low skewed to the left, with some probabilities peaking at 0.65

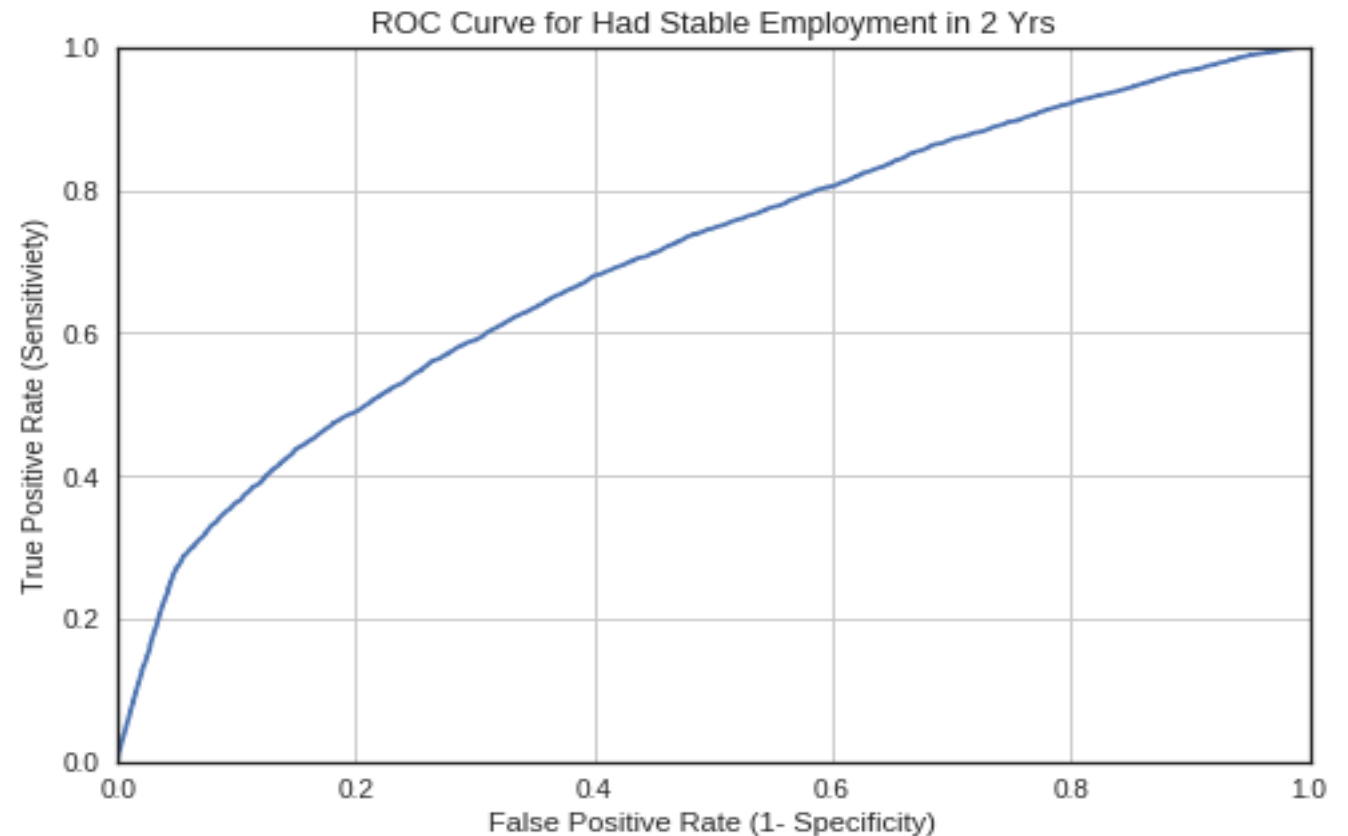


We chose to use a default threshold of 0.5 based on this chart

# ROC curve

The tradeoff between sensitivity (the probability of predicting a real positive will be a positive) and 1-specificity (the probability of predicting a real negative will be a positive) is not too close to 45° line (chance) – accurate test.

Area under ROC curve = 0.7



We ran 6 models and found that Logistic Regression gave us the best results for Illinois

Extra Trees  
Classifier

Random  
Forest  
Classifier

Gaussian

Logistic  
Regression

K Nearest  
Neighbor

Gradient  
Boosting

Logistic regression performed best:

Test Accuracy :: 0.7928

Confusion matrix ::  $\begin{bmatrix} 25232 & 1094 \\ 5982 & 1842 \end{bmatrix}$

Classify error = 0.2072

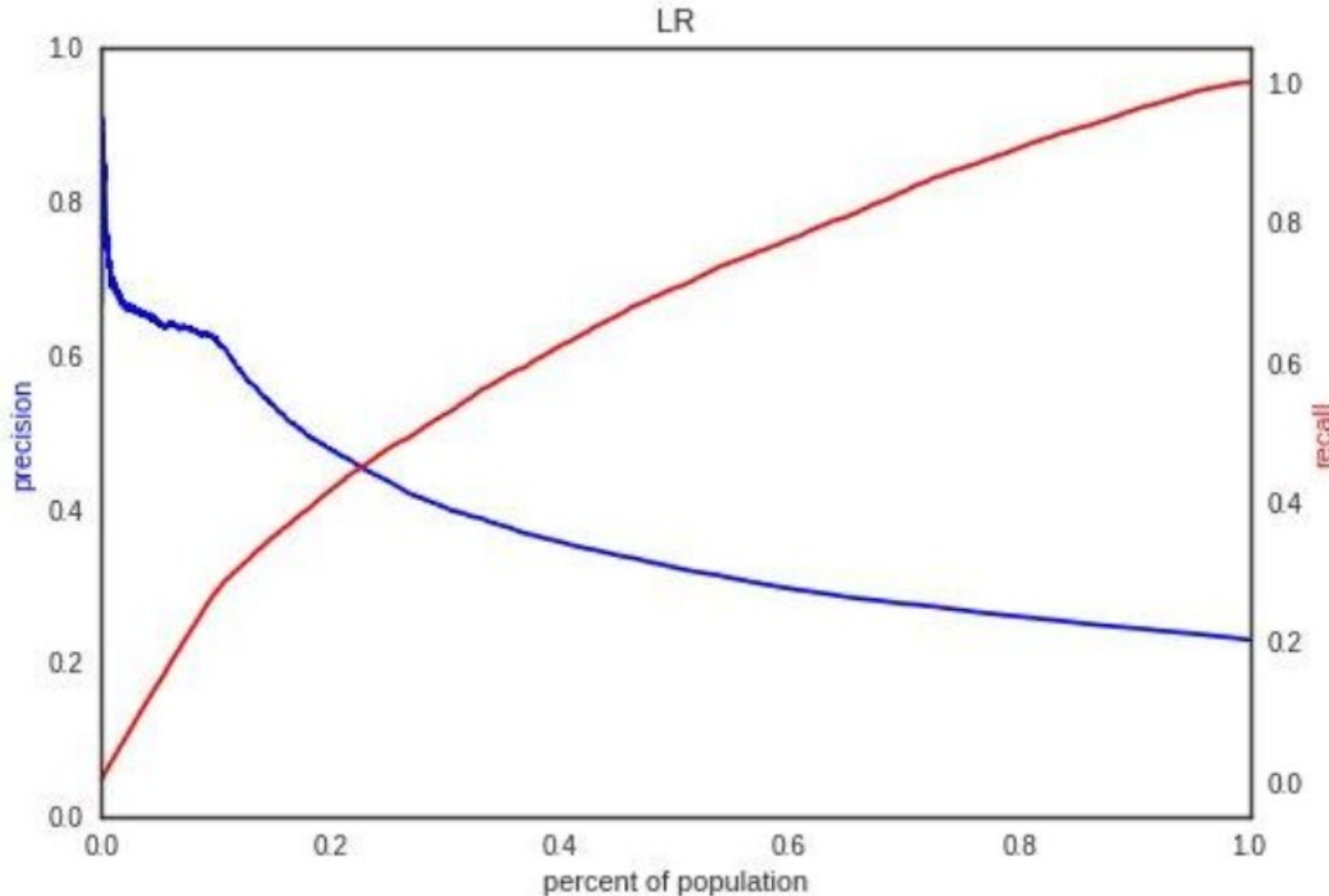
Precision = 0.6274

Recall= 0.2354

Specificity= 0.9584

false-positive rate= 0.0416

# Logistic Regression for Illinois stable employment



- We see that recall improves with the increase of population.
- Precision decreases with an increase in population, but much more gradually.
- **Practical Interpretation:** Budgets are tight in IL DOC, so perhaps we would want to stop our intervention at 22% of our population to maximize recall at 43% and not sacrifice too much precision. If we target 10% of the population, we improve recall significantly (30%) and not lose much of precision (65%).

Now let's add Missouri wages

# Adding Missouri model

- Having additional wage records data from Missouri, we decided to see if any ex-offenders who are not finding employment in Illinois and live in the bordering counties with Missouri, find stable employment in Missouri within 8 quarters after release from prison in Illinois.
- Count of stable employment = 321
- Additional feature = pre-prison stable employment in Missouri
- Split into train and test set

Missouri	
Test	3,433
Train	6,969

# Generalized Linear Model Regression Results

```

=====
Dep. Variable:          stableemp      No. Observations:          6969
Model:                  GLM           Df Residuals:                6949
Model Family:           Gaussian      Df Model:                    19
Link Function:          identity      Scale:                      0.0261790516798
Method:                  IRLS         Log-Likelihood:              2814.8
Date:                   Mon, 25 Jun 2018    Deviance:                    181.92
Time:                   23:23:39          Pearson chi2:                 182.
No. Iterations:         2
=====

```

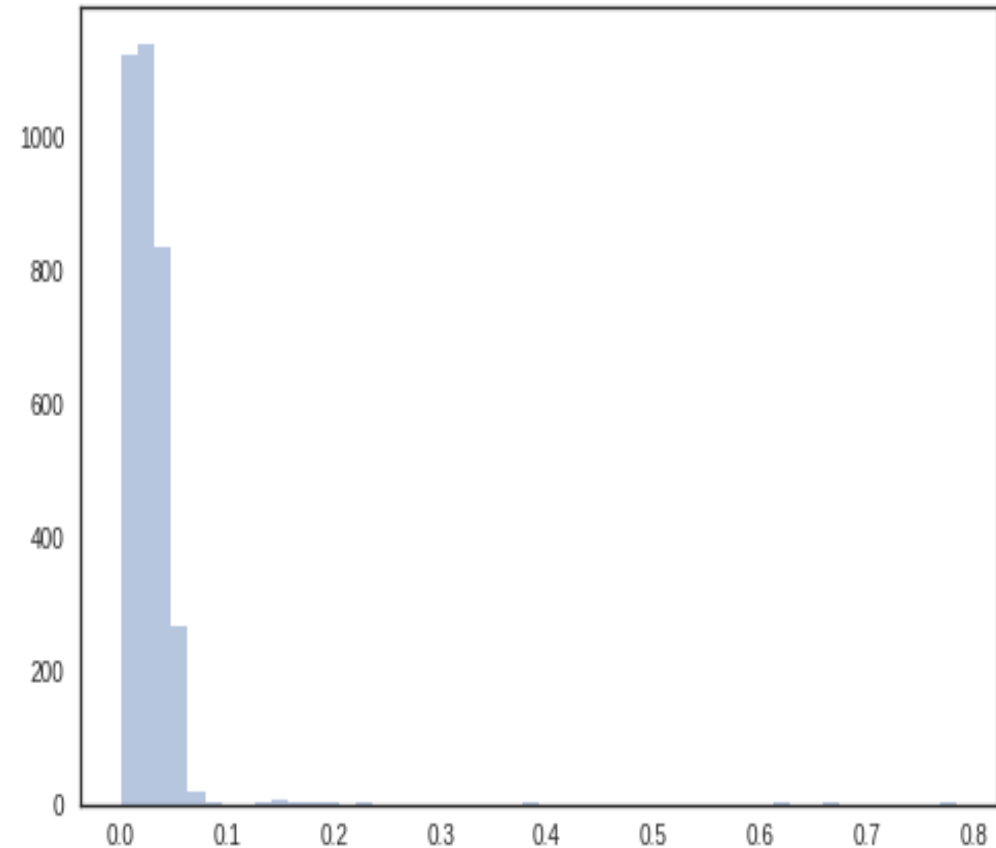
	coef	std err	z	P> z	[0.025	0.975]
-----						
preprisonemp	0.0120	0.008	1.516	0.130	-0.004	0.028
sex_F	-0.0030	0.008	-0.398	0.690	-0.018	0.012
race_BLK	-0.0010	0.010	-0.100	0.920	-0.020	0.018
race_WHI	-0.0014	0.010	-0.139	0.890	-0.021	0.018
race_HSP	0.00694	0.020	3.385	0.001	0.029	0.110
ingang	0.0211	0.005	4.243	0.000	0.011	0.031
haskids	0.0063	0.004	1.420	0.156	-0.002	0.015
married	-0.0415	0.081	-0.512	0.609	-0.200	0.117
age	8.115e-05	0.000	0.388	0.698	-0.000	0.000
educlevel	0.0091	0.004	2.260	0.024	0.001	0.017
class	0.0097	0.004	2.322	0.020	0.002	0.018
offence	-0.0101	0.004	-2.374	0.018	-0.018	-0.002
vetflag	-0.0024	0.009	-0.265	0.791	-0.020	0.016
drugalcflag	-0.0098	0.006	-1.533	0.125	-0.022	0.003
drugcocflag	-0.0203	0.007	-3.086	0.002	-0.033	-0.007
drugampflag	-0.0029	0.009	-0.328	0.743	-0.021	0.015
drugmarflag	0.0059	0.007	0.866	0.387	-0.007	0.019
drugherflag	-0.0023	0.010	-0.224	0.823	-0.022	0.018
drugpcpflag	-0.0117	0.019	-0.606	0.544	-0.050	0.026
preprisonemplmo	0.5319	0.021	25.094	0.000	0.490	0.573

Change in pre-prison employment in Missouri has a 53% effect on stable employment, if all other features are held constant.

# Histogram of predicted values

Probability of stable  
employment is very low  
skewed to the left

We chose to use a threshold of  
0.05 based on this chart

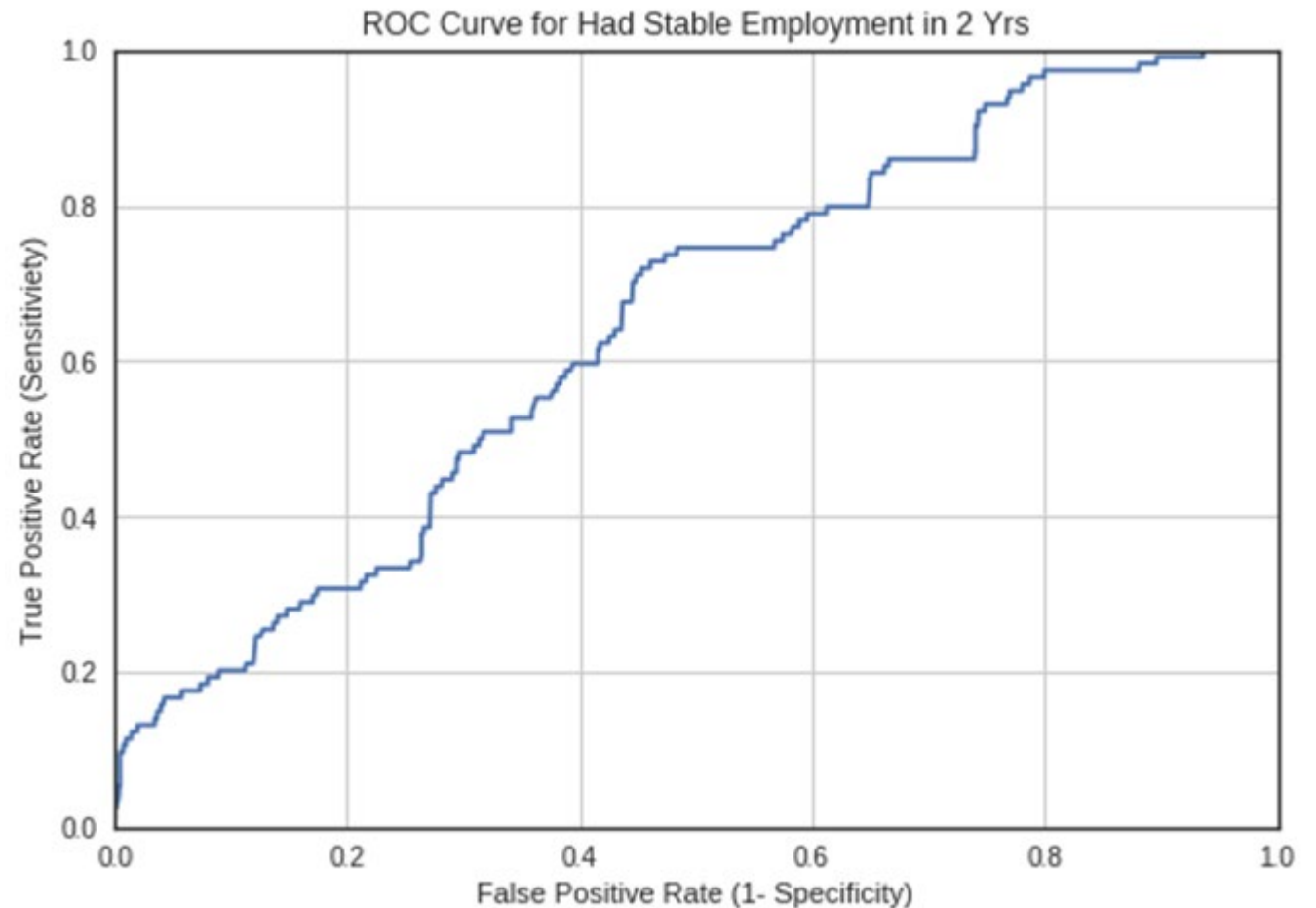




# ROC curve

The tradeoff between sensitivity (the probability of predicting a real positive will be a positive) and 1-specificity (the probability of predicting a real negative will be a positive) is not too far from 45° line (chance) – less accurate test.

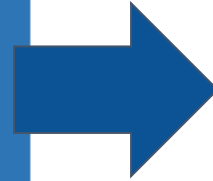
Area under ROC curve = 0.65



We ran six models and found that Random Forest Classifier gave us the best results for Missouri

Extra Trees  
Classifier

Random  
Forest  
Classifier



Gaussian

Logistic  
Regression

K Nearest  
Neighbor

Gradient  
Boosting

Random Forest Classifier performed best:

Test Accuracy :: 0.9694

Confusion matrix ::  $\begin{bmatrix} 33 & 01 & 18 \\ 87 & 27 \end{bmatrix}$

Classify error = 0.1054

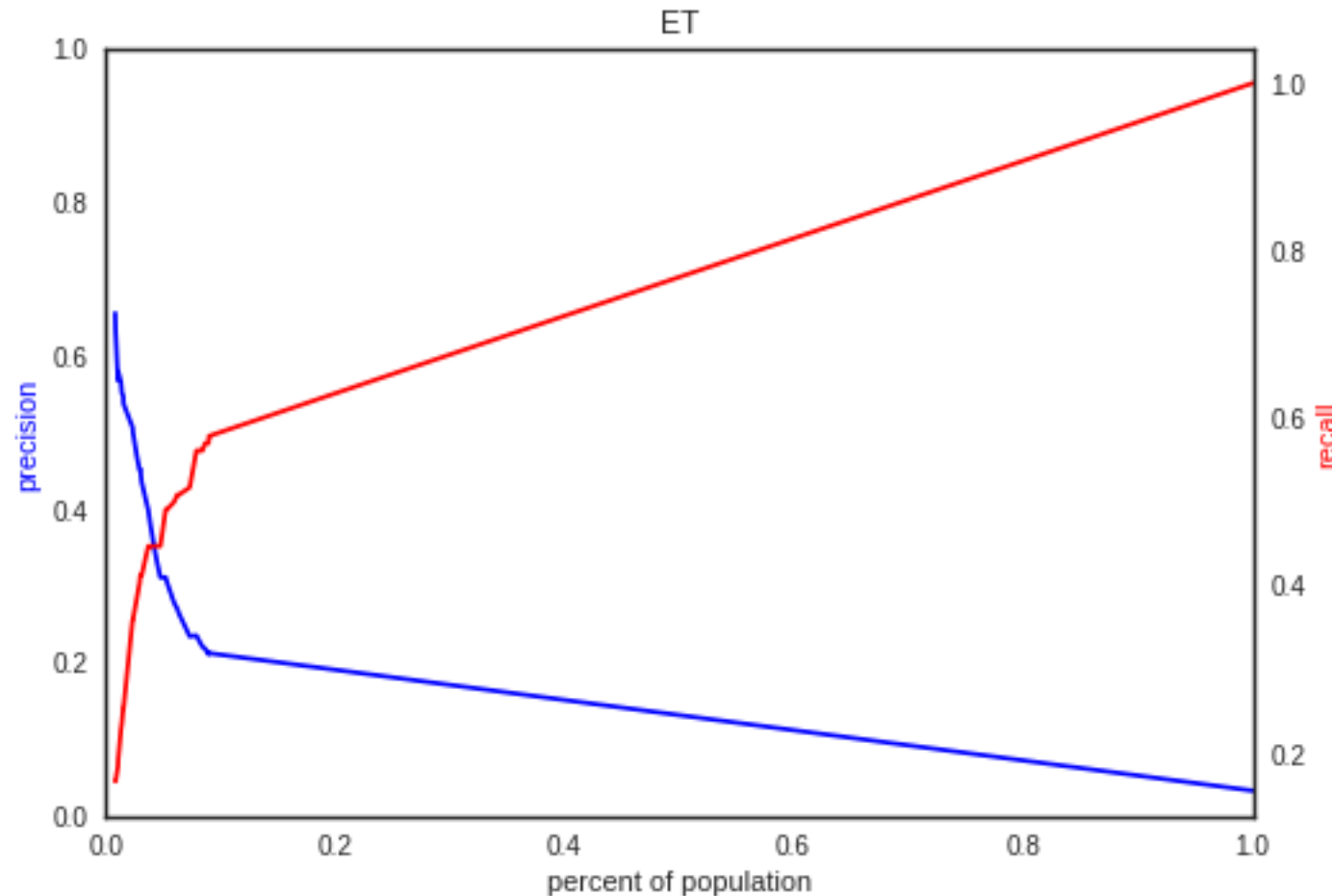
Precision = 0.0753

Recall= 0.1930

Specificity= 0.9187

false-positive rate= 0.0813

# Random Forest Classifier

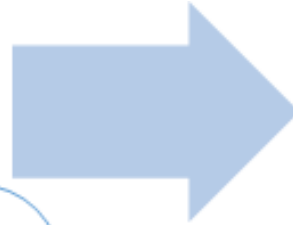


- We see that recall improves with the increase of population.
- Precision decreases with an increase in population, but much more gradually.
- **Practical Interpretation:** Budgets are tight in IL DOC, so perhaps we would want to stop our intervention at 5% of our population to maximize recall at 35% and not sacrifice too much precision.

# Practical Results

## Intervene with everyone

- If we intervene with all individuals who did not have employment before their imprisonment, it may increase their chances of having steady wages post-prison;
- however, this large-scale intervention may also be impractical and costly.



## Focus on 10-20%

- We would want to focus on this population in Illinois
- Focus on 5% of population incarcerated near a border county who are expected to find jobs in Missouri

# Next Steps for a future analysis:

- Describe the factors present for the population who did earn wages pre-prison in order to move intervention up. In a perfect world, we'd also be able to predict why someone who earned wages would then also be incarcerated and potentially interpret that trajectory.
- **Include other features in our analysis (length of prison stay, education programs in prison)**
- Communicate our findings back to the researchers from our literature review
- **Prepare network analysis of employers that hire ex-offenders**