# Study of French labour market and inequalities

L. Insolia, J. Kim and Y. Yeghikyan

SNS

— Midterm results —

March 14, 2018

## **Objectives**

- Structure of French labour market
- Inequalities (in terms of salary):
  - ages
  - gender
  - job categories
  - spatial distribution
- Firms' distribution
- Exploratory analyses

## Methodology

#### INSEE data

- Population: age, sex and cohabitation mode
- Salary: job categories, age and sex (mean net salary per hour in €)
- Firms: number of firms for each size
- Geography: GPS location

for different geographical levels (communes, departments, towns) in 2014

GitHub repo: https://github.com/LucaIns/TSL

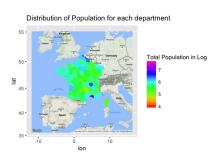
## What has been done so far . . .

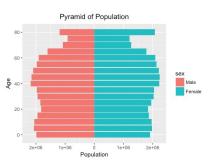
# Pre-processing phase

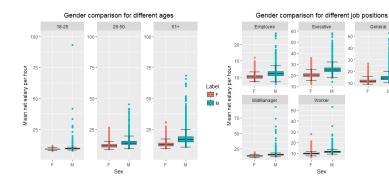
0

...

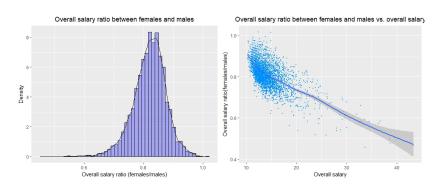
## Demographic profiles

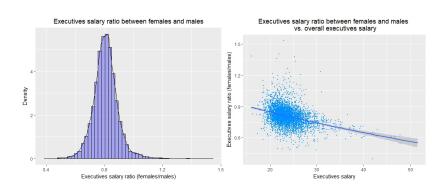


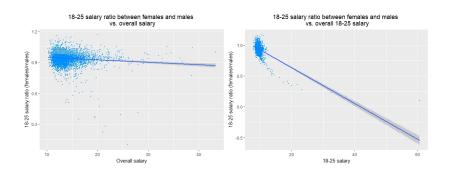




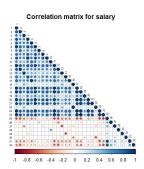
Label

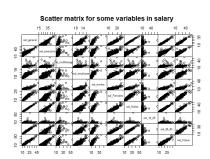




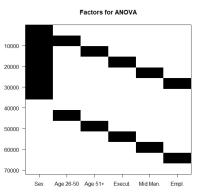


#### Bivariate relations



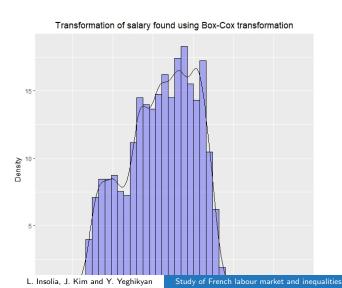


## ANOVA using sex, job, age and interaction effects

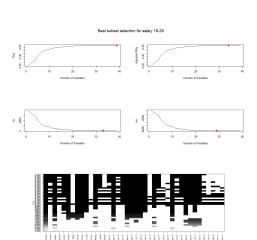


```
lm(formula = sal_v ~ sal_sex + sal_age + sal_iob + sal_sex:sal_age +
    sal_sex:sal_job)
Residuals:
                      Median
-0.084405 -0.004353 0.000683 0.005477 0.057842
Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)
                 1.061e-01 8.471e-05 1252.443 < 2e-16 ***
sal sex
                 -1.097e-02 1.198e-04 -91.569 < 2e-16 ***
sal_agel
                 -2.160e-02 1.467e-04 -147.227
sal age2
                 -2.838e-02 1.467e-04 -193.440
sal_jobl
                 -5.601e-02
                            1.467e-04 -381.776
sal iob2
                 -3.036e-02
                            1.467e-04 -206.917
                 -8.621e-03 1.467e-04 -58.758 < 2e-16 ***
sal_job3
sal sex:sal agel -2.502e-03 2.075e-04
sal_sex:sal_age2 -7.572e-03 2.075e-04
                                       -36.491 < 2e-16 ***
sal sex:sal jobl 1.197e-03 2.075e-04
sal_sex:sal_job2 4.873e-04 2.075e-04
sal sex:sal job3 3.059e-03 2.075e-04
                                        14.742 < 2e-16 ***
Signif, codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.008585 on 71892 degrees of freedom
Multiple R-squared: 0.841, Adjusted R-squared: 0.841
 -statistic: 3.458e+04 on 11 and 71892 DF. p-value: < 2.2e-16
```

## ANOVA using sex, job, age and interaction effects

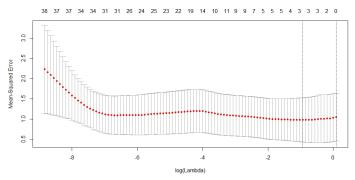


## Prediction for young people using BSS

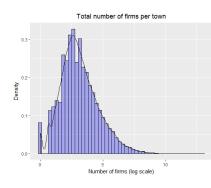


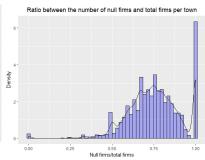
## Elastic net and and 10-folds CV

#### Best lambda for salary 18-25 using elastic net with alpha=0.5 and 10-folds CV

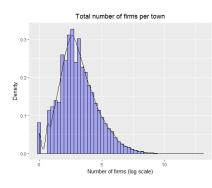


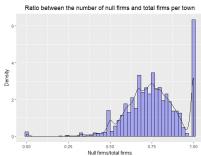
## Distribution of firms per town



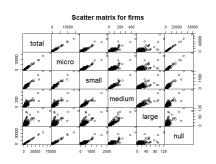


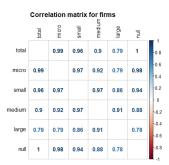
## Distribution of firms per town





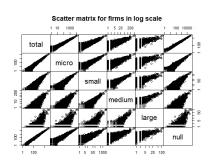
#### Bivariate relations





#### **Excluding Paris**

## Bivariate relations



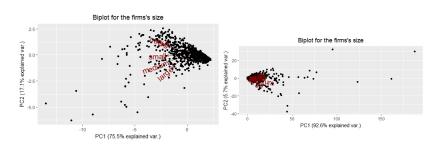
#### Correlation matrix for firms in log scale

	total	micro	small	mediun	large	100	_
total		0.93	0.79	0.61	0.39	0.99	-0
micro	0.93		0.83	0.64	0.41	0.9	- o
small	0.79	0.83		0.8	0.54	0.76	-0
medium	0.61	0.64	0.8		0.71	0.59	(
large	0.39	0.41	0.54	0.71		0.39	-(
null	0.99	0.9	0.76	0.59	0.39		(

#### **Including Paris**

## **PCA**

#### Using original data scaled (not logs) Most typical vs. Excluding just Paris



#### Issues

- A lot of NA in geo locations (retrieved from Google API)
- Unique code for salary data 1/7 of the total
- Missing additional information
- French DOM-TOM regions
- Outliers and spatial correlation
- Combine the separated datasets

#### Future works

- Create meaningful indicators
- Take correlation into account (especially spatial)
- Perform clustering techniques to identify geographical clusters
- Perform groupwise lasso to predict salary data
- Verification/improvement of the obtained results
- Compare the methodologies used with robust ones
- Find complementary datasets

# - Thank you -