Sant'Anna
School of Advanced Studies – Pisa

INSTITUTE
OF ECONOMICS

# Vanishing social classes?
# Facts and figures of the Italian labor market.

**Armanda Cetrulo**,* Angelica Sbardella^ and Maria Enrica Virgillito*
*Institute of Economics, Scuola Superiore Sant'Anna
^Centro Studi e Ricerche Enrico Fermi

Cetrulo, A, Sbardella, A and M.E. Virgillito (2021) Vanishing social classes? Facts and figures of the Italian labour market. *Sant'Anna School of Advanced Studies LEM working paper series 2021/29*.

**INAPP Online Seminar**
17/02/2022

# Motivation

- Increasing inequality in advanced economies (*Atkison et al., 2011; World inequality report, 2022*).
- Analysis on social classes largely dismissed in Italy (despite *Sylos Labini, 1974*).
- Explosion of the pandemic underlined the relevance of socio-economic stratifications and the role of occupations in explaining them (*Cetrulo et al., 2022*).
- The goal of this paper is to intersect three interrelate dimensions:
    1. wage inequality
    2. socio-demographic attributes
    3. occupational categories

through the lens of social classes theory (*Wright, 2000; Goldthorpe, 2002*) and institutional change (*Michel and Bivens, 2021*).

# Research questions

1. Which are the factors that help to explain increasing wage inequality in Italy in the last thirty years?

2. Are social classes really vanishing nowadays?

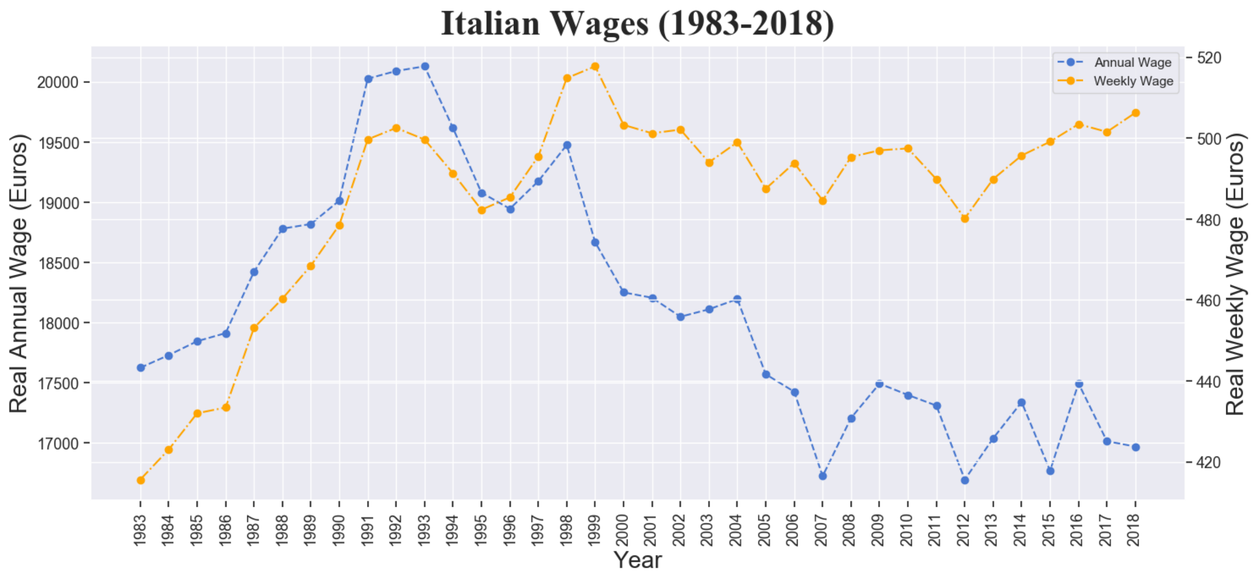
# Data

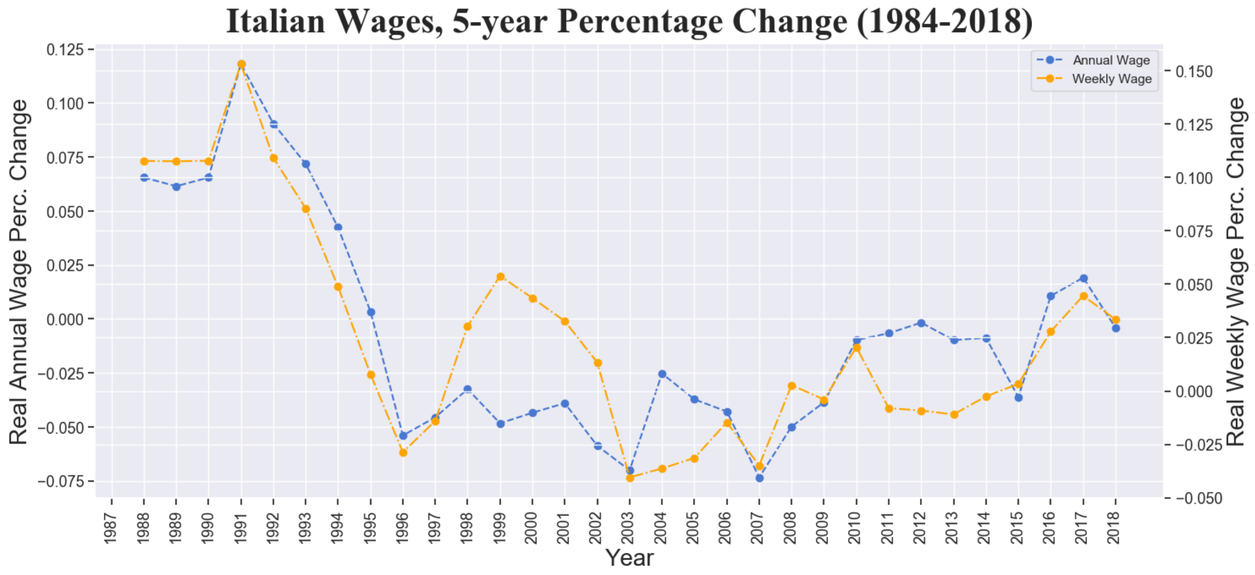
| Variable | Unit | Description | Period |
|---|---|---|---|
| Number of jobs | Number | / | 1983-2018 |
| Number of first jobs | Number | / | 1983-2018 |
| Gender | Dummy | *Female/Male* | 1983-2018 |
| Geographical Area | Categorical | *North-West, North-East, South, Central, Islands* | 1983-2018 |
| Regions | Categorical | *Italian regions* | 1983-2018 |
| Job Class | Categorical | *Trainees, Blue-collars, White-collars, Executives, Middle Managers* | 1983-2018 (Middle Managers from 1998) |
| Employment contract | % job | *Full time/part time* | 1985-2018 |
| Employment contract | % job | *Permanent/temporary* | 1998-2018 |
| Sectors (1 digit Ateco 2007) | % job | / | 1983-2018 |
| Working weeks | Average | *Number of weeks* | 1983-2018 |
| Yearly gross wage | Average | / | 1983-2018 |

INPS - Rapporti di lavoro annuali: micro-level database on administrative records.
Representative sample of employees of the private sector (no agricultural and domestic jobs) from 1983 to 2018

# Macro trends

## *Wage compression*



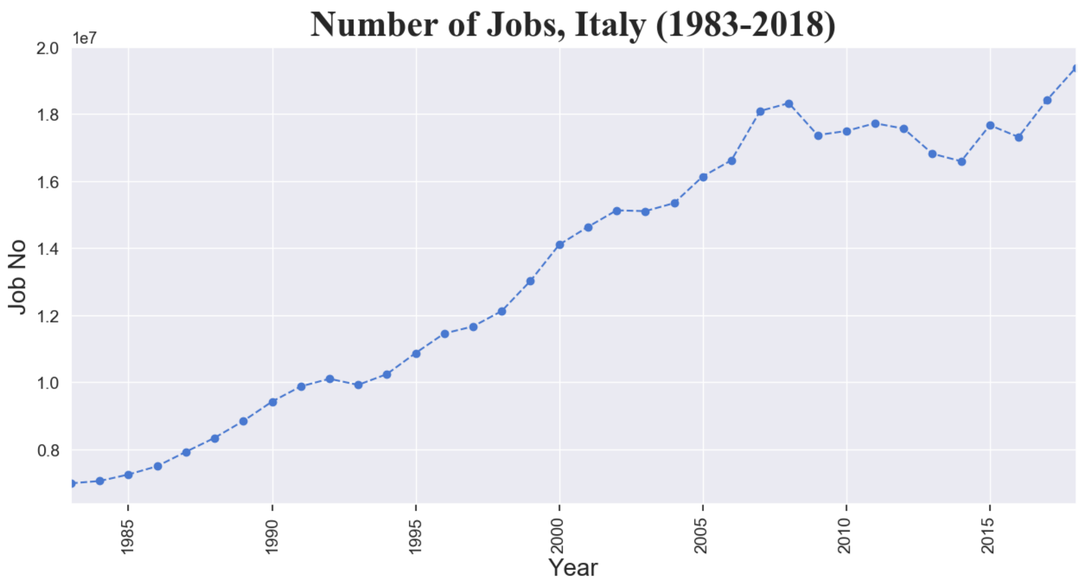

- Wage increasing trend in the decade 1983-1993
- Max increase at 12,5%
- Overall declining trend since 1993
- Strong decoupling between yearly and monthly wages starting from 1998

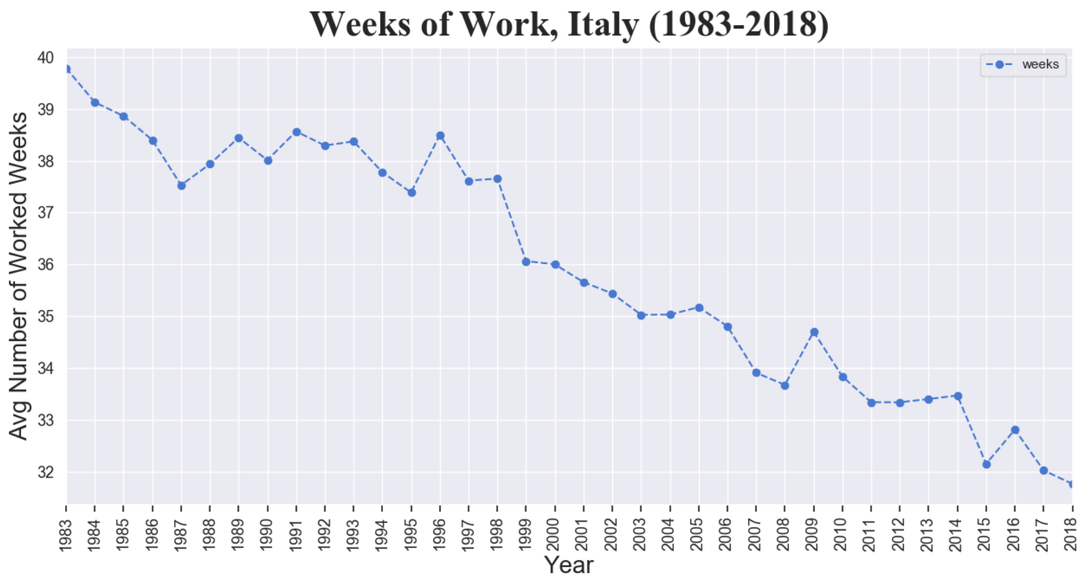
Tightly linked to institutional and legislative changes

- 83-92 process of abolition of wage indexation to inflation
- 1993 Protocollo Ciampi
- 1997 Pacchetto Treu
- 2003 Legge Biagi

# Macro trends

*Job flexibility and fragmentation*



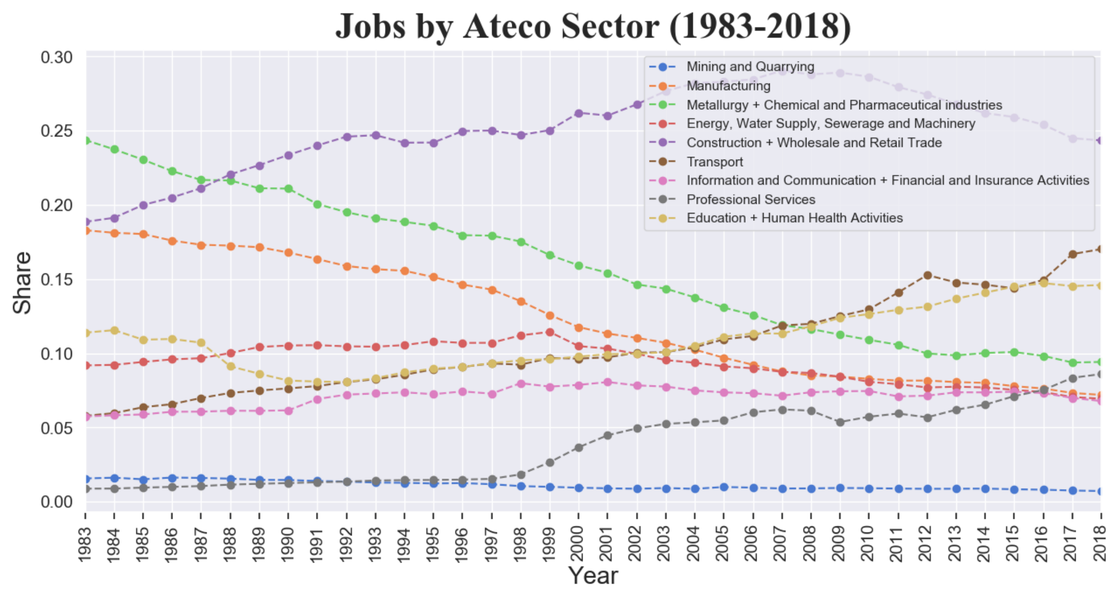

- Reduced number of working weeks
- Increasing number of jobs

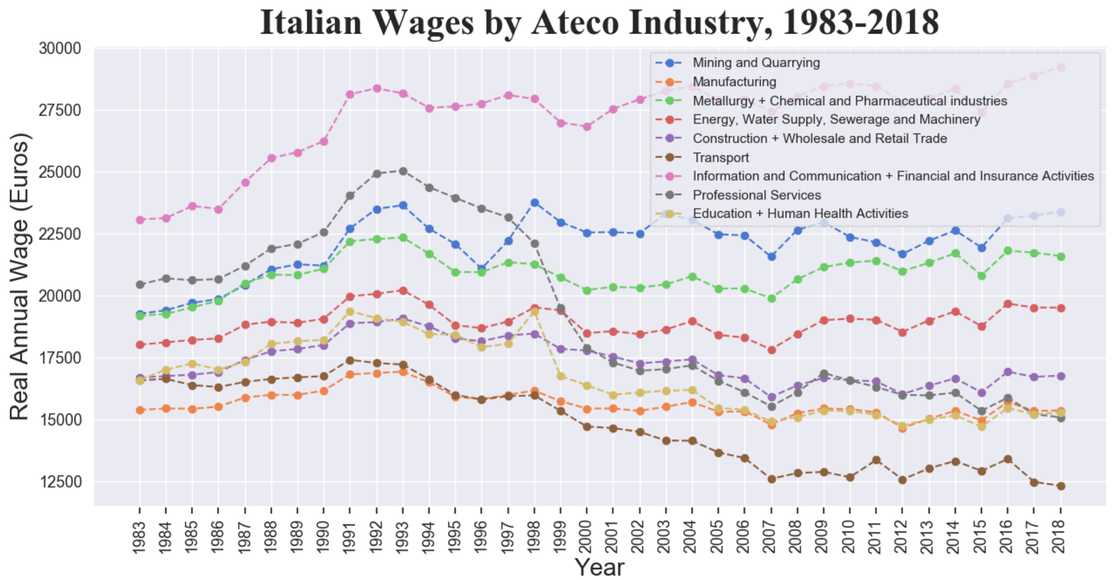
Tightly linked to institutional and legislative changes in the name of flexsecurity:

- 1993 Protocollo Ciampi
- 1997 Pacchetto Treu
- 2003 Legge Biagi
- 2012 Legge Fornero
- 2014 Jobs Act

# Macro trends

## *Deindustrialization and Servitization*



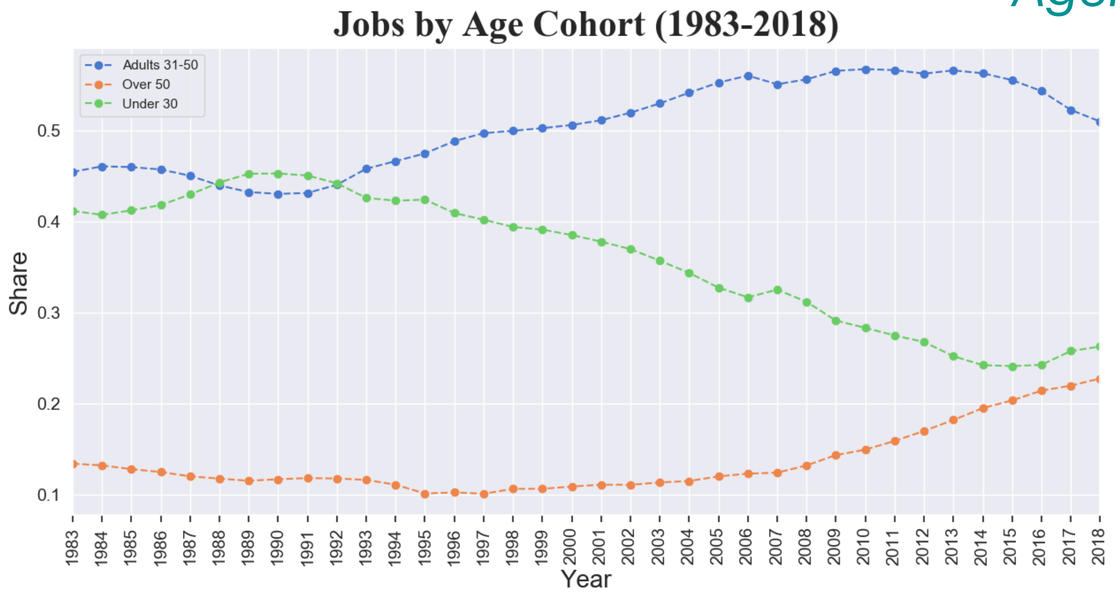



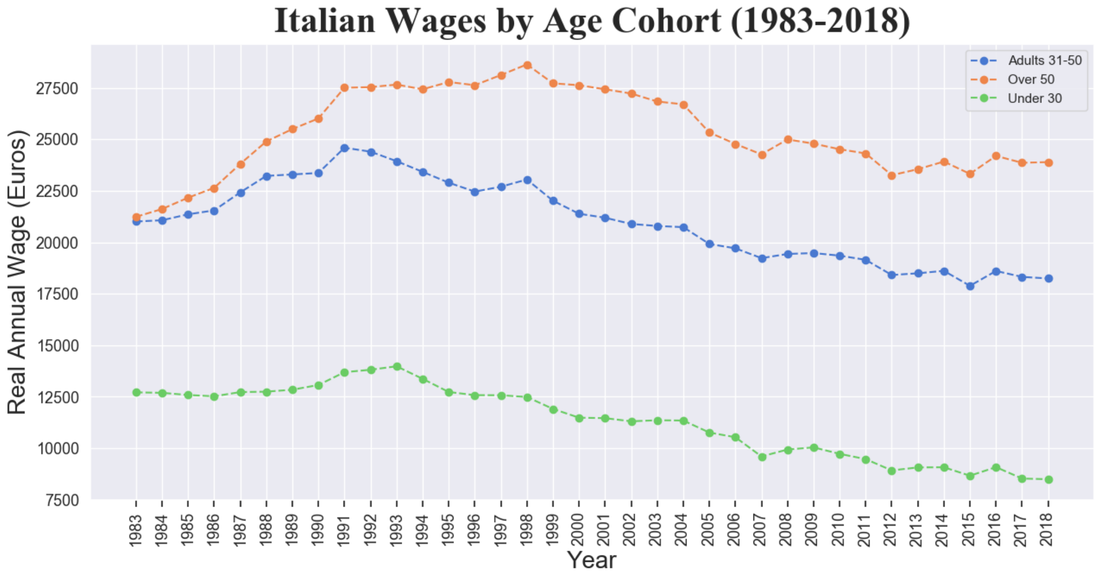

- Deindustrialization pattern: shares in manufacturing (orange), chemical, metallurgy and pharma (green) strongly declining from 0.20% and 0.25% in 1983 respectively to approximately 10% in 2018.

- Tertiarization trend: increasing shares of retail trade (purple line), transport (brown line), education and human health activity (yellow) occupying more than fifty percent of the entire labour force in 2018.

# Macro trends

*Ageing labour force*

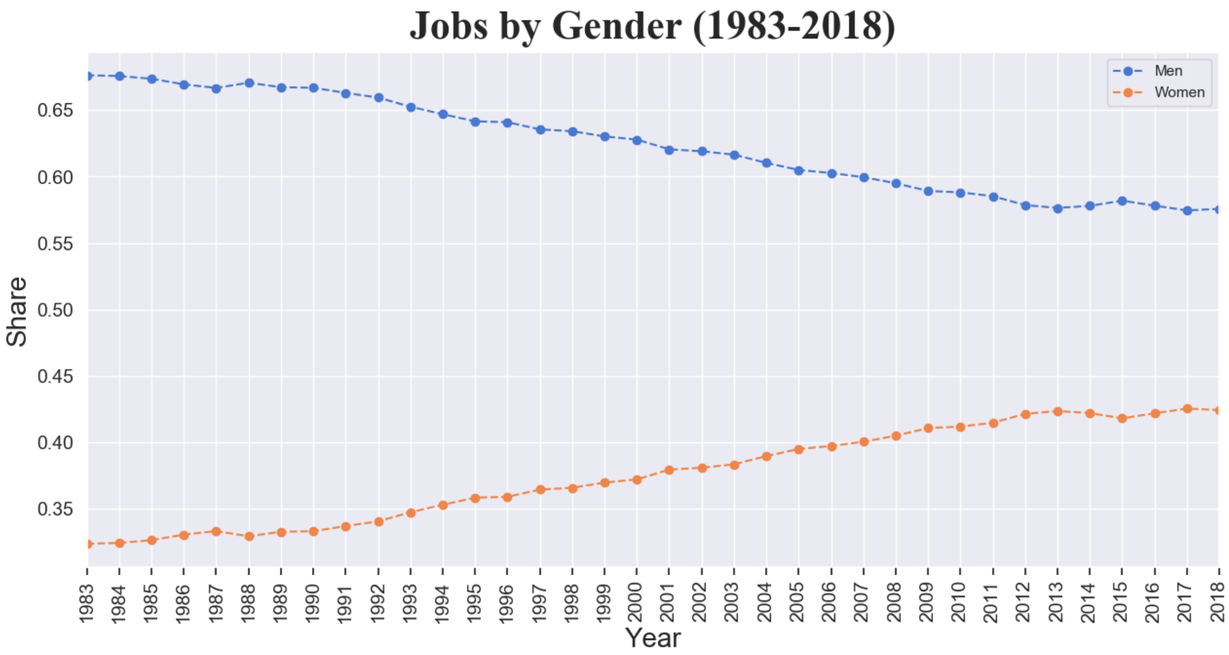


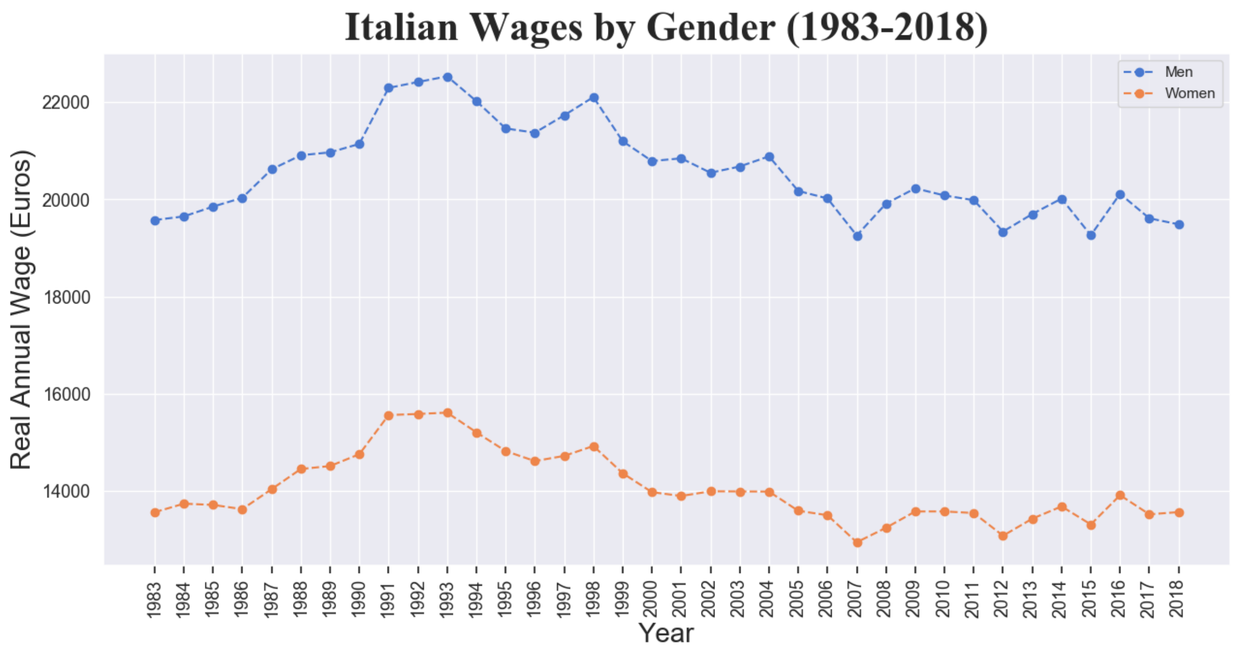




- Increasing participation of 31-50 years old workers since 1992.
- Declining trend in the share of workers under 30 years.
- Growing fraction of workers over 50 populating the labour market since 1998.
- Remarkable wage premium for the older segment.
- Declining remuneration of under 30 (in 2018 earn on average less than 10 thousand euros yearly).

# Macro trends

*Gender divides*

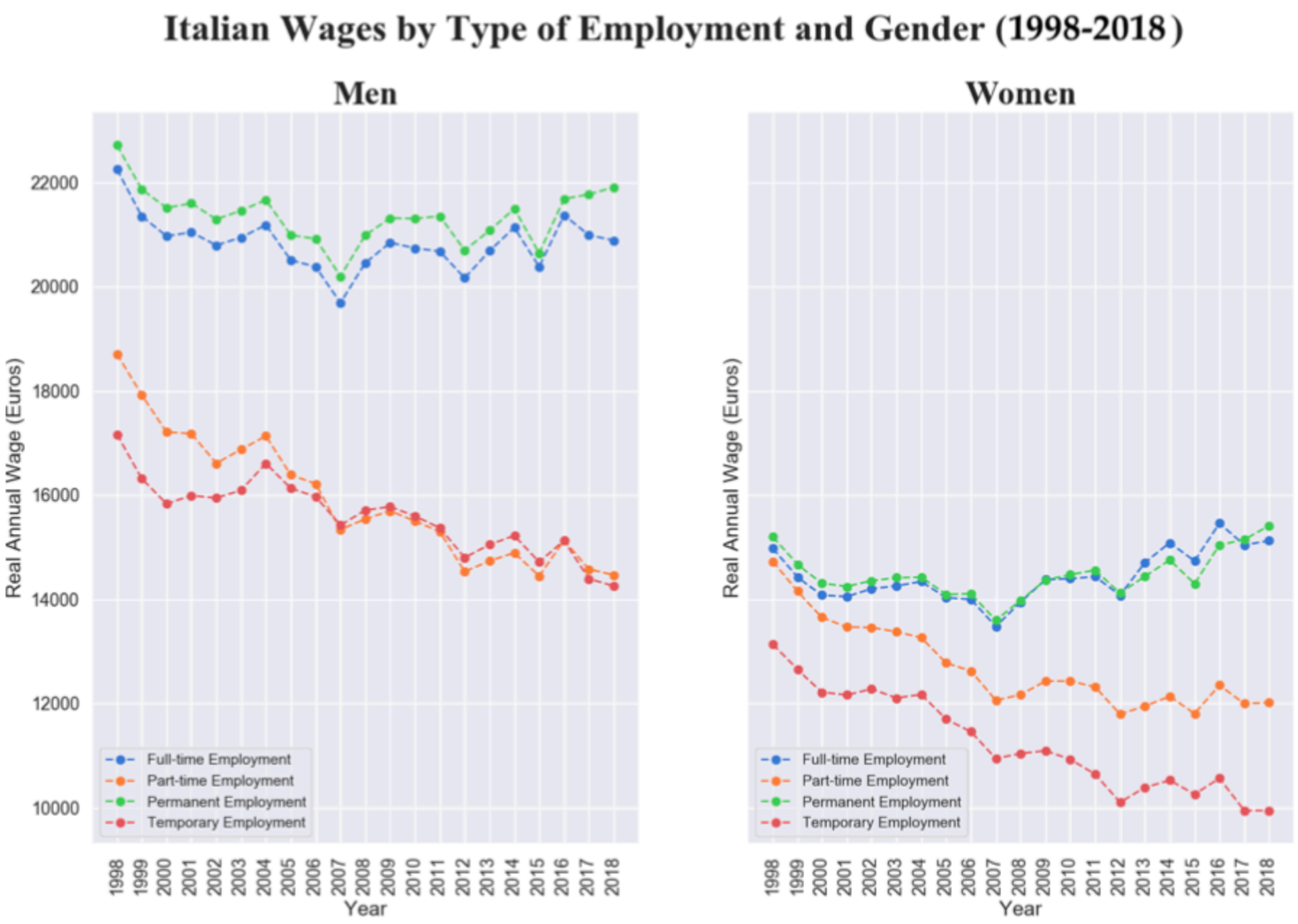



- Growing participation of female workers in the labour market, with a share raising from 35% in 1983 up to 42% in 2018.
- Constant gender-pay gap of approximately 6 thousands euros yearly wage.

# Macro trends

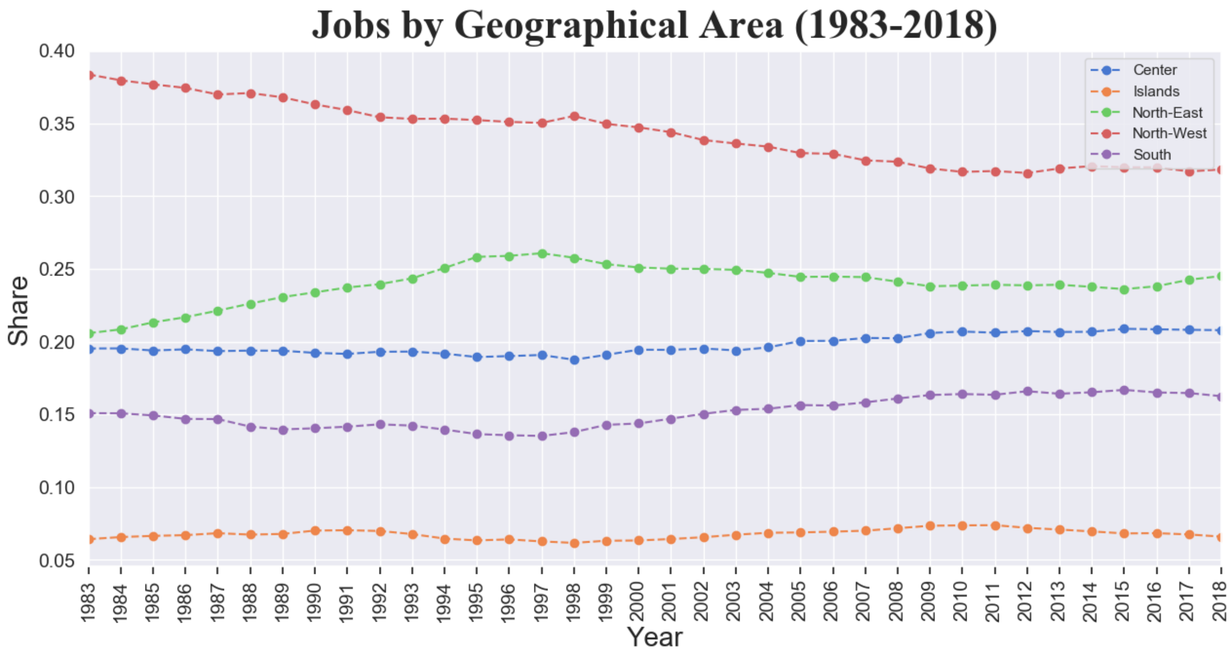
*Gender divides and type of employment*

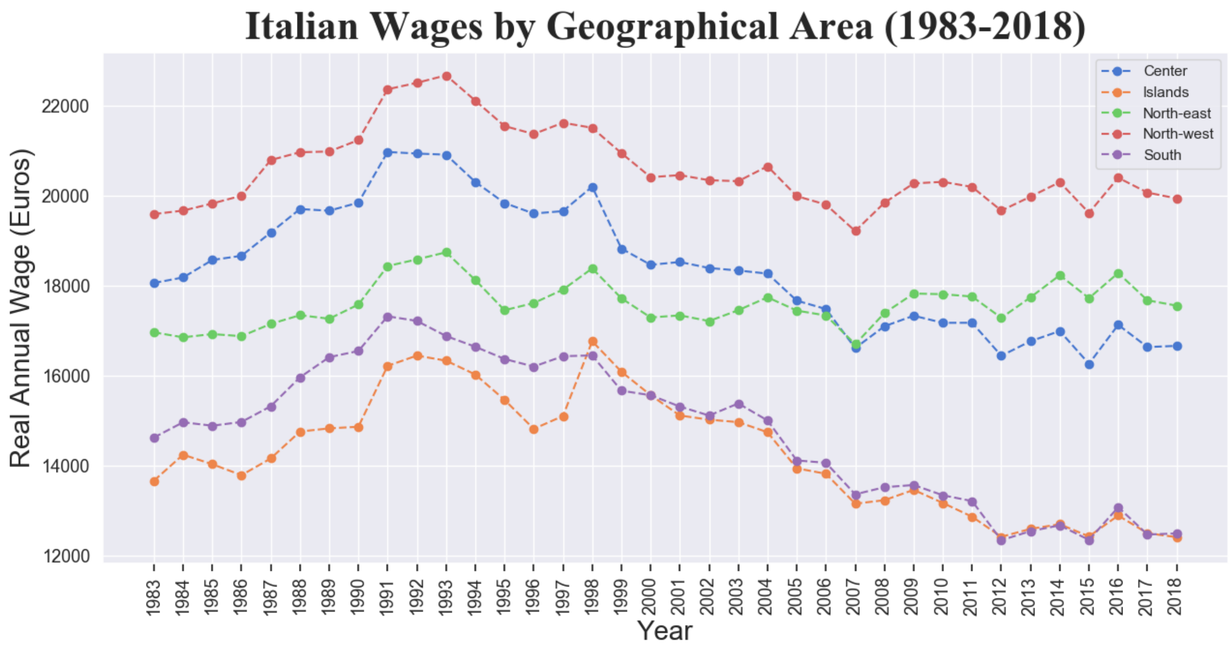



- Declining wage trend in temporary/part-time jobs for both male and female workers.
- Temporary female workers experiencing the lowest remunerations across all categories.

# Macro trends

## *Geographical divergence*



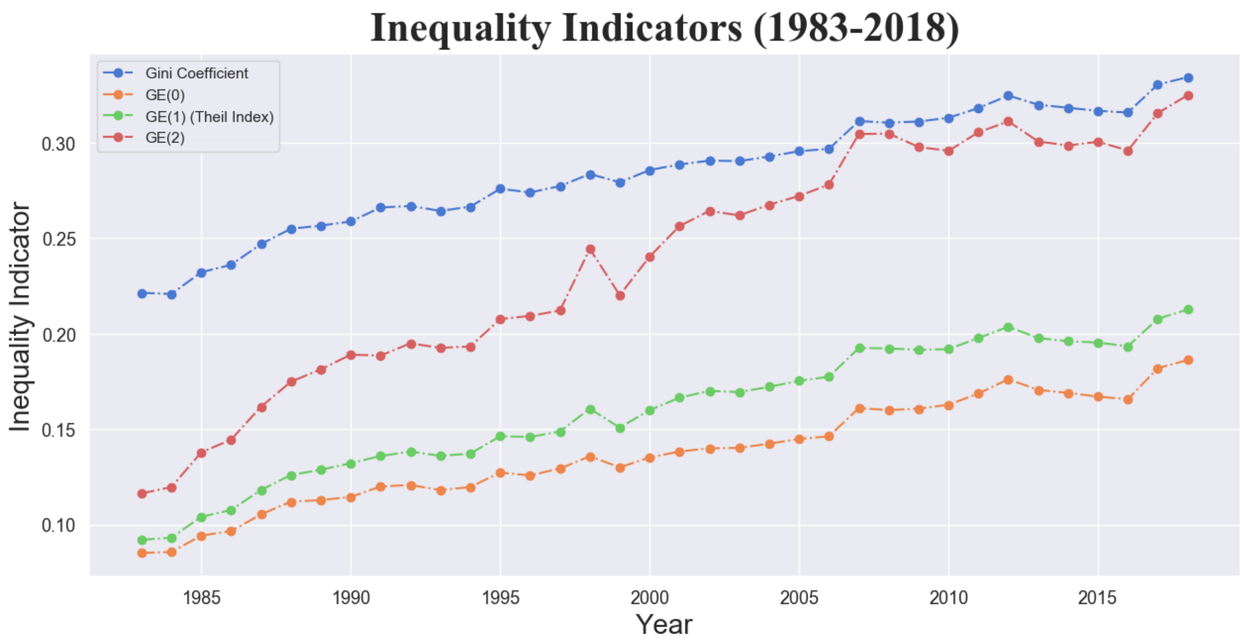




- Job shares remain roughly constant (north-west decreasing and south increasing).
- Declining trend in the wages of South and Islands.
- Marked pattern of wage divergence accelerating since 1998.

# Facts and figures of the Italian labor market

- Wage compression
- Job Flexibilization and Fragmentation
- Deindustrialization and Servitization
- Ageing Labour Force
- Feminization and Gender Divide
- Geographical Divergence

*Exploding Inequality*




Analysis consistent with several studies on the Italian economy (*Rosolia, 2010; Bloise and Ricci, 2018; Brandolini et al., 2018 Franzini and Raitano, 2019*).

# Inequality indicators

*Gini coefficient*

For a population of n individuals and a discrete wage distribution $y \in R^n_+$, where each worker has wage $y_i$, $(i = 1, \cdots, n)$ and wages are indexed in non-decreasing order $(y_i \leq y_{i+1})$, the Gini coefficient formulation we employ is defined as follows:

$$G = \frac{n+1}{n} - \frac{2}{n \sum_{i=1}^{n} y_i} \left( \sum_{i=1}^{n} (n+1-i)\, y_i \right)$$

where G= 0 in the case of perfect equality, i.e. when all individuals have the same wage, G = 1 in a situation of maximum inequality, i.e. when a single individual earns the totality of wages. The Gini coefficient tends to be more sensitive to wage differences around the mode than in the lower or higher tails of the distribution (Green et al., 1994).

# Inequality indicators

## *Generalised Entropy Indicator*

Mathematically, considering a population of n individuals, with wage $y_i$ (i = 1, · · · , n), arithmetic mean income m, sample weight, if present, equal to $w_i$ with $f_i = w_i/N$ and $N = \Sigma\, w_i$ ($N = n$ when $w_i = 1$), these widely used inequality indicators are defined as follows:

$$GE(\alpha) = \begin{cases} \frac{1}{\alpha(\alpha-1)} \sum_{i=1}^{n} f_i \left[ \left( \frac{y_i}{m} \right)^{\alpha} - 1 \right], & \alpha \neq 0, 1, \\ \frac{1}{n} \sum_{i=1}^{n} f_i \frac{y_i}{m} \ln \frac{y_i}{m}, & \alpha = 1, \\ \frac{1}{n} \sum_{i=1}^{n} f_i \ln \frac{m}{y_i}, & \alpha = 0 \end{cases}$$

We focus on $GE(\alpha)$ with $\alpha \in [0, 1, 2]$, where $GE(0)$, $GE(1)$, $GE(2)$ correspond respectively to the *Mean Logarithmic Deviation* (MLD), the *Theil Index* and the *Half Square of the Coefficient of Variation* (1/2 SCV).

| Year | Gini | MLD (GE(0)) | Theil (GE(1)) | 1/2 SCV (GE(2)) |
|---|---|---|---|---|
| 1983 | 221 | 85 | 92 | 116 |
| 1993 | 264 | 118 | 135 | 192 |
| 2003 | 290 | 140 | 169 | 261 |
| 2013 | 319 | 170 | 197 | 300 |
| 2018 | 334 | 186 | 212 | 324 |

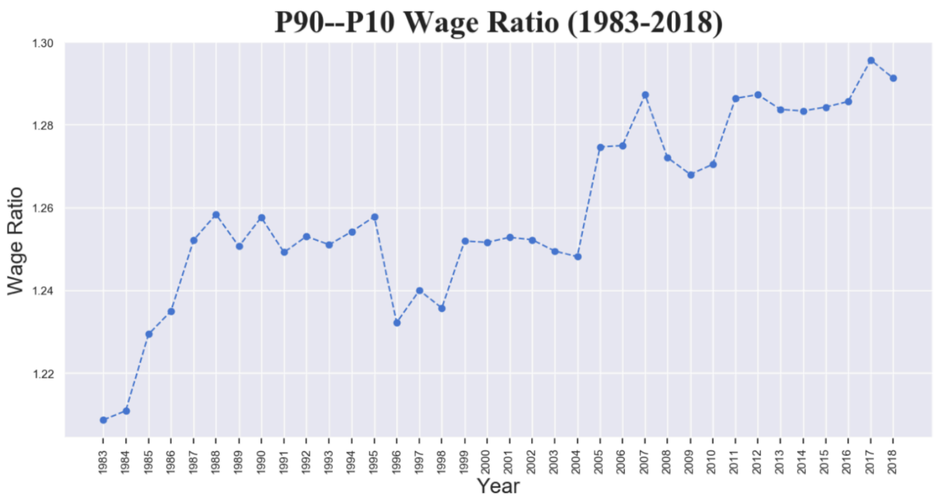
*Gini Coefficient and selected general entropy indicators GE(α) multiplied by 1000*

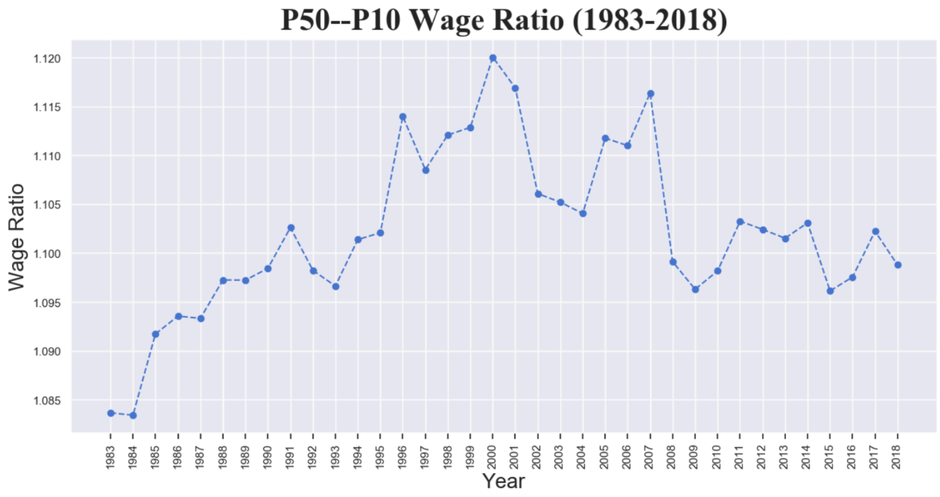
| Time Interval | Gini | MLD (GE(0)) | Theil (GE(1)) | 1/2 SCV (GE(2)) |
|---|---|---|---|---|
| 1983-1993 | 19 | 39 | 46 | 65 |
| 1993-2003 | 9 | 19 | 25 | 36 |
| 2003-2013 | 1 | 21 | 16 | 15 |
| 2013-2018 | 5 | 9 | 8 | 8 |
| 1983-2018 | 51 7 | 119 | 130 | 179 |

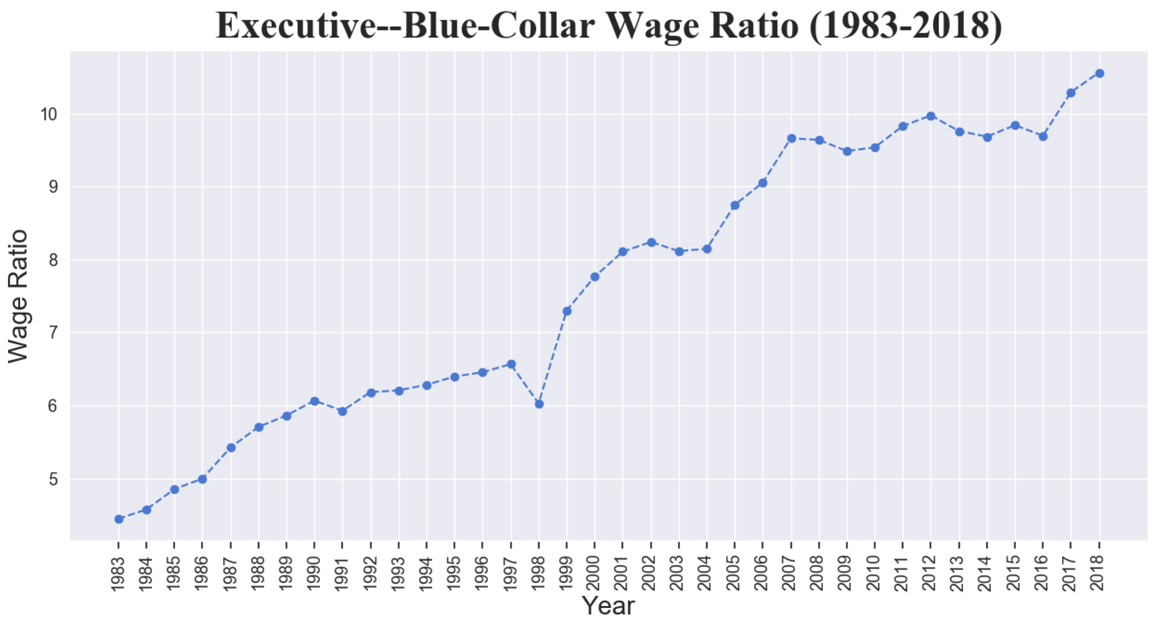
*% change of the Gini Coefficient and the selected general entropy indicators*

# Rising wage inequality

*Divergence at the top, convergence towards the bottom are mirrored by occupations wage pattern*



# Inequality decomposition by sub-groups

*Model*

Following Jenkins (1995), we exploit the decomposability proprieties of the Generalized Entropy indicators:

$$\mathbf{GE(\alpha) = GE^{W}(\alpha) + GE^{B}(\alpha)}$$

$GE^{W}(\alpha)$ = within group inequality (weighted sum of inequalities in each subgroup)

$GE^{B}(\alpha)$ = between group inequality (inequality remaining assuming each worker's income is equal to his sub-group's mean income)

We focus on Ge(0) *Mean Logarithmic Deviation* and Ge(2) *Half Square of Coefficient Variation*

**Through this empirical exercise, we observe how inequality can be explained by differences within and between groups.**

# Inequality indicators

## *Decomposition*

Following Jenkins (1995), we consider a population divided into *m* groups, each with *nk* individuals with *k=1, ...., m* **GE(α)= GE$^{W}$(α) + GE$^{B}$(α)** can be rewritten as :

$$GE(0) = GE(0)^W + GE(0)^B = \sum_k^m v_k\, GE(0)^{(k)} + \sum_k^m v_k\, log(1/s_k)$$
$$GE(2) = GE(2)^W + GE(2)^B = \sum_k^m v_k\, s_k^2\, GE(2)^{(k)} + \sum_k^m v_k[s_k^2 - 1]$$

where *vk = nk/n* is the population share of group *k*, *sk=yk/y* is the ratio of the average group wage to overall average wage, $GE^{(k)}(\alpha)$ with α =0,2 is the inequality index for each group k and accounts for the inequality between the members of the group that is assumed to be a separate population from the other groups.

# Inequality decomposition by sub-groups

*Results*

| | | 1983 | 1993 | 2003 | 2013 | 2018 |
|---|---|---|---|---|---|---|
| **Gender** | *GE(0) Within* | 71 | 103 | 123 | 153 | 170 |
| | *GE(0) Between* | 14 | 15 | 17 | 17 | 16 |
| | *GE(2) Within* | 103 | 179 | 245 | 284 | 310 |
| | *GE(2) Between* | 13 | 13 | 16 | 16 | 14 |
| **Age Cohort** | *GE(0) Within* | 55 | 79 | 91 | 116 | 119 |
| | *GE(0) Between* | 30 | 39 | 49 | 54 | 67 |
| | *GE(2) Within* | 89 | 156 | 218 | 257 | 271 |
| | *GE(2) Between* | 27 | 36 | 43 | 43 | 53 |
| **Geographical Area** | *GE(0) Within* | 78 | 111 | 134 | 156 | 172 |
| | *GE(0) Between* | 7 | 7 | 6 | 14 | 14 |
| | *GE(2) Within* | 110 | 186 | 256 | 287 | 311 |
| | *GE(2) Between* | 6 | 6 | 5 | 13 | 13 |
| **Occupational Category** | *GE(0) Within* | 39 | 39 | 43 | 60 | 70 |
| | *GE(0) Between* | 46 | 79 | 97 | 110 | 116 |
| | *GE(2) Within* | 45 | 52 | 51 | 53 | 63 |
| | *GE(2) Between* | 71 | 140 | 210 | 247 | 261 |

- **Within inequality** is high and increasing over time in sub-groups defined by *gender, age class and geographical area.*

- **Between inequality** is higher than within inequality only in the case of *occupational categories.*

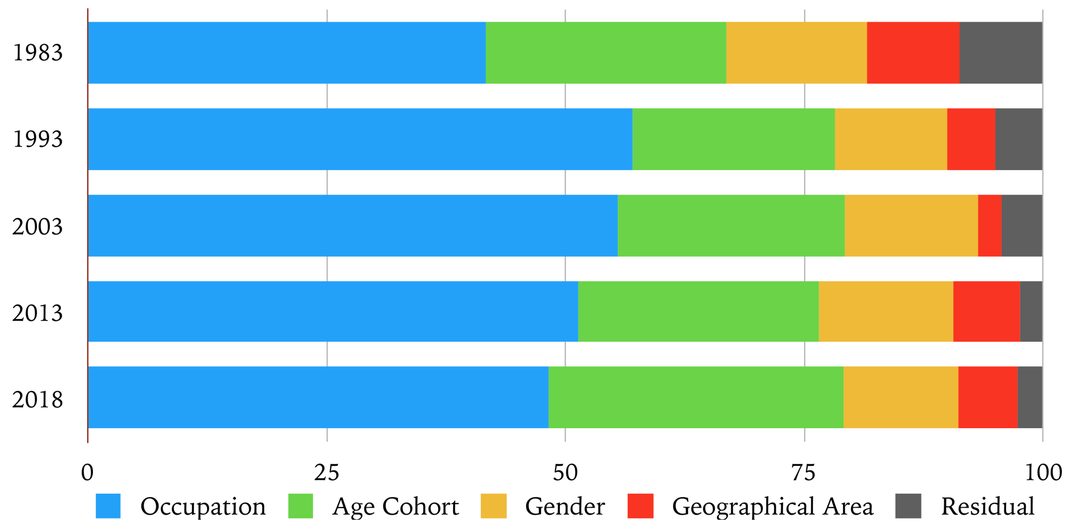
# Regression based inequality decomposition

Following Fields (2003), *log(yi)* is the log-wage generating function, where *yi* is the wage of id *i*, *xij* the *j-th* explanatory variable, *sj (log(y))* is te share of the wage log-variance (the relative factor inequality weight) of the *j-th* explanatory factor.

$$log(y_i) = aZ_i$$
$$a = [\alpha \quad \beta_1 \quad \beta_2 \quad \dots \quad \beta_k \quad 1]$$
$$Z_i = [1 \; x_{i1} \; x_{i2} \quad \dots \quad x_{ik} \; \epsilon_i]$$

$$s_j(log(y)) = \frac{cov[a_j Z_j, log(y)]}{\sigma^2(log(y))}$$

**Sum of the relative contribution in each subgroup**




All variables have statistically significant coefficients. **Occupations** display the **highest relative factor inequality weight**, followed by age and gender.

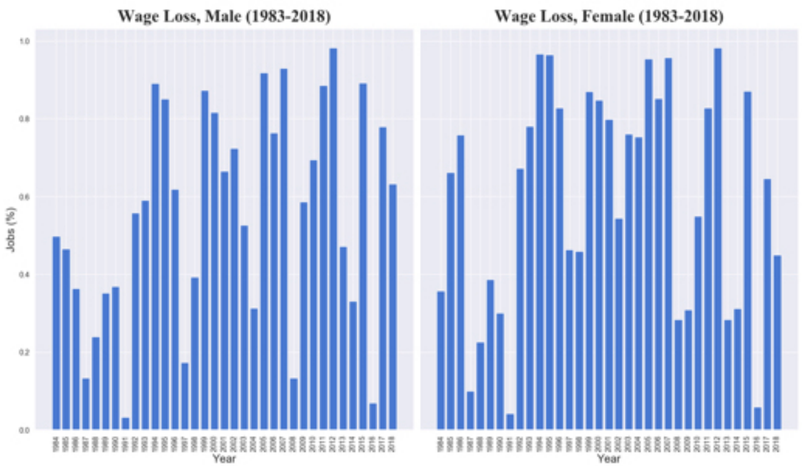
# Wage losses

*Do wage losses correlate with workforce attributes?*

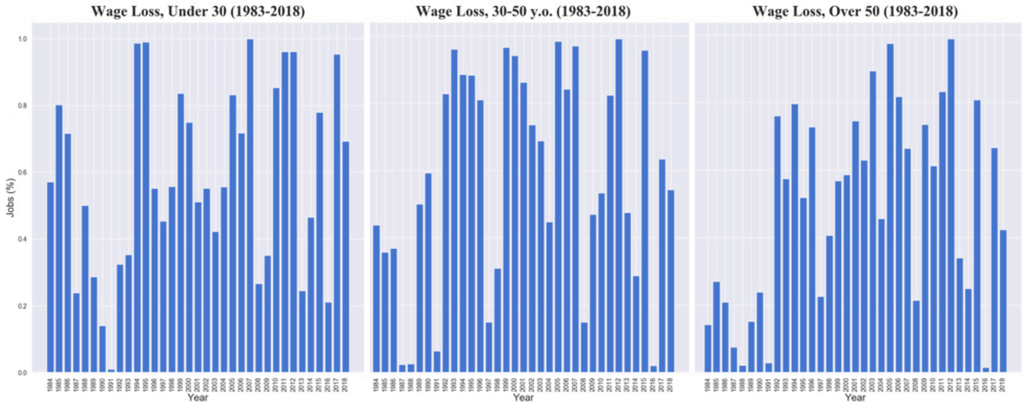
- We attribute a panel structure to our data, with *id* given by the intersection of job class, gender, age and geo area.
- Then, we compute the annual wage growth and we focus on wage loss events.
- We test whether the distribution of the event across the population group is independent from workforce partition.
- We find strong evidence of dependence, implying that the probability of recording a wage loss is not independent from “individual" attributes such as gender, age, geographical area and job class.

# Wage losses

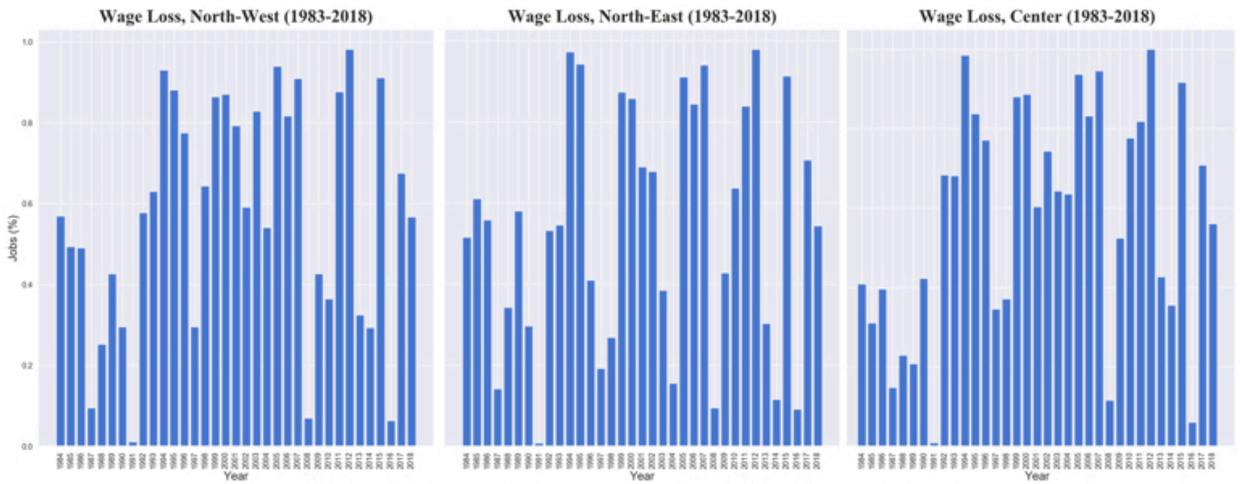
*By gender, age cohort and geographical area*

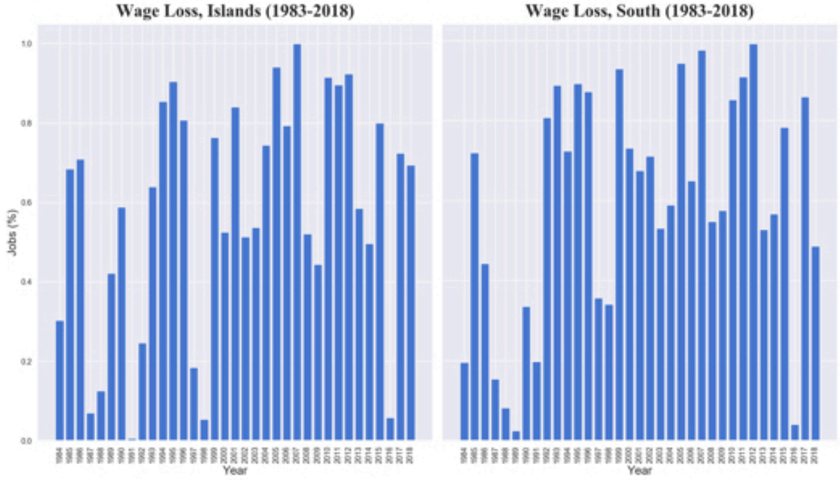



***Wage loss by gender***




***Wage loss by age groups***

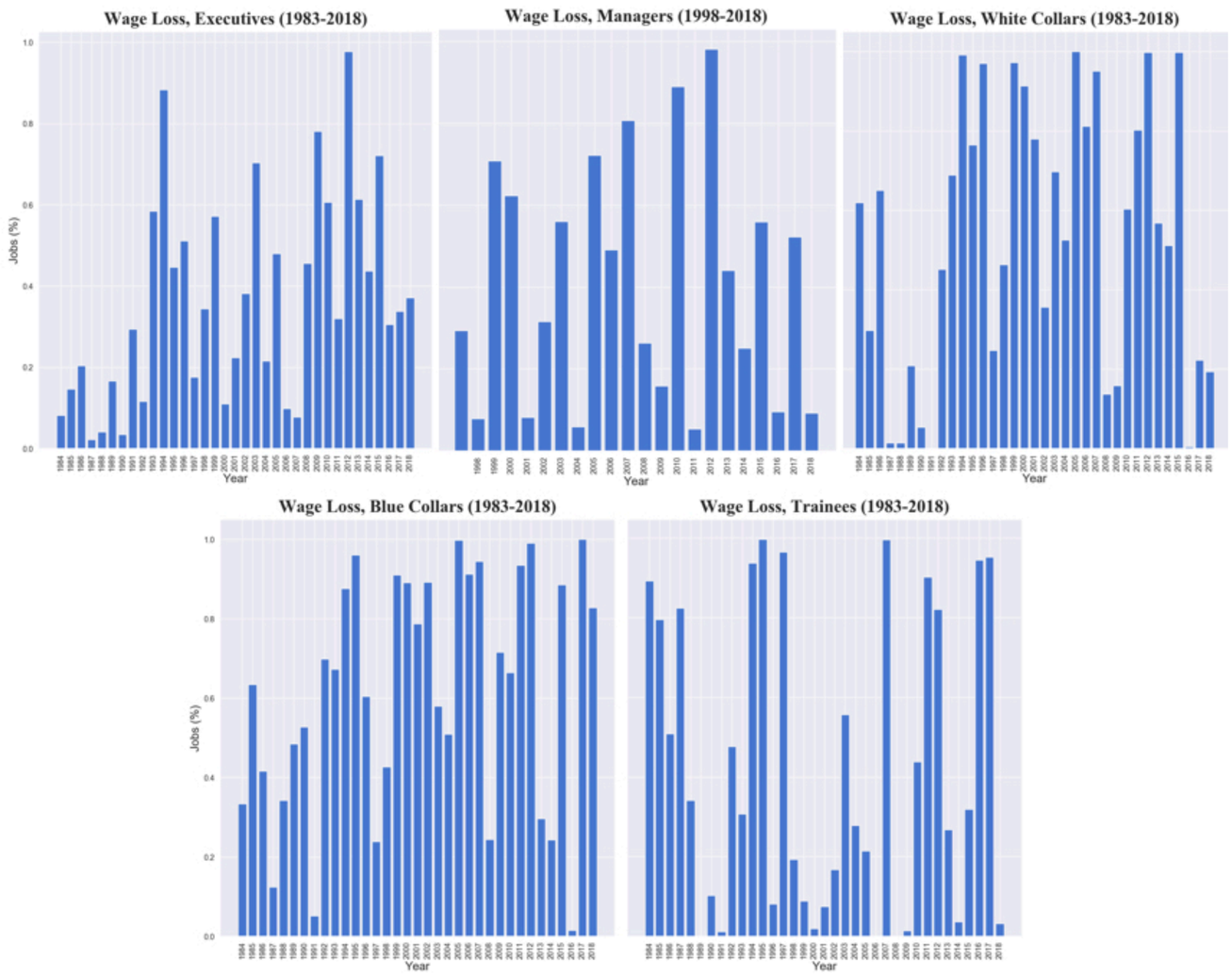



***Wage loss by geographical area***

# Wage losses

*By occupational categories*

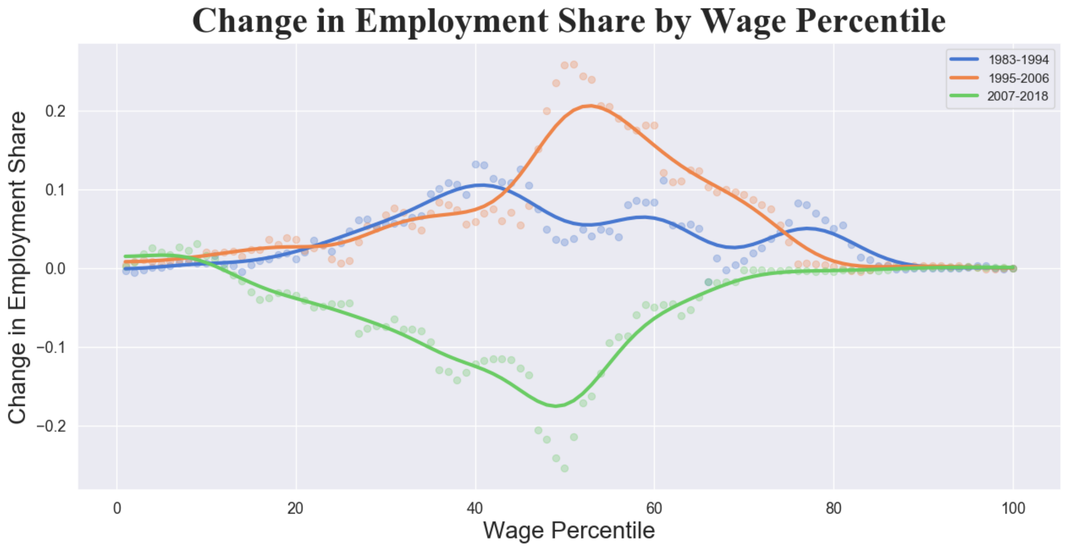


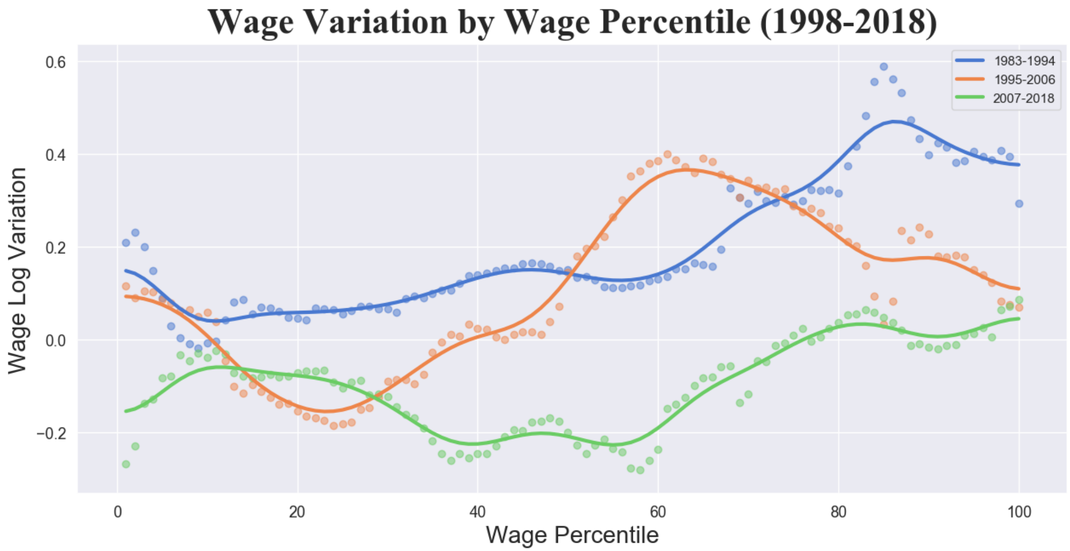

- Negative wage growth event (blue area) is very common especially after the first decade.
- Losses more concentrated across female and youth jobs.
- Northern regions more resilient to loss events.
- Blue & white collars record the highest losses.

# Job polarization

## *Why inequality is not a matter of technology*

Locally weighted Gaussian-smoothing regression of changes in employment and wage shares by wage percentile rank as proxy for occupational skill (Acemoglu and Autor, 2011). For each wage percentile *i*, the employment share is defined as $E_{i,t}/E_t$. $E_{it}$ is total employment in percentile *i* and year *t*, $E_t$ is total employment in year *t*. We then plot the change $E_{i,t}/E_t - E_{i,t0}/E_{t0}$. A similar procedure is followed for wages.




**No U-shaped pattern in *employment changes*:** in the first two periods hump-shaped pattern recording increases in the middle part of the income distribution, in the last decade decrease in the middle part but with no increase nor in the lower neither in the upper part of the wage distribution (as predicted by RBTC). With respect to *wages*, **gradual downward wage compression** occurring over the entire period, during the last period a generalized negative wage growth along the entire wage distribution, except wages at the very top.

# Concluding remarks

- General trend of **exploding inequality** at the top and convergence toward the bottom of the wage distribution, no descriptive evidence of job polarization *(Oesch, 2022)* but rather of generalized **wage compression (***Michel and Bivens, 2021)*.
- **Inequality as institutionally driven**: labor market deregulation determined strong job precariousness and fragmentation (*Piasna and Meant, 2017*), that coupled with an overall deindustrialization trend and tightened generational, geographical and gender asymmetries.
- **Social classes**, broadly framed as occupational categories, turn to be fundamental in explaining increasing wage inequality (*Albertini, 2013, Brandolini et al., 2018, Penissat, 2020*).
- Focus on occupations and employment relations, allowing to identify macro trends and understand how different dimensions of social stratification contribute to explain wage distribution and intersect with each other.

# Possible follow-up

- Link socio-economic data with industrial, innovation and regional data.
- Combined analysis on the role of gender and occupations segregation over wage inequality (*Scott et al., 2010; Rubery and Hebson, 2018)*.
- Investigation over heterogeneity within macro-occupational groups through more disaggregated data (*Gallie, 1996, Weeden and Grutsky, 2005, Oesch, 2006)*.

# Grazie!

armanda.cetrulo@santannapisa.it