Labor Market Segmentation & the Income Distribution: New Evidence from Internal Census Bureau Data

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Disclaimer

The research in this paper was conducted while all authors were Special Sworn Status researchers of the U.S. Census Bureau at the Rocky Mountain Research Data Center at the University of Colorado. **Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.**

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- **Limits the RDC allows us to overcome:**
  - Public-use data is top-coded; RDC data is not.*

*Actually, it is, but the top-code limits are higher.

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  - Public-use data is top-coded; RDC data is not.
  - Expansion in coverage (1975 - 2017)
  - More comprehensive consideration of models

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  - Fully non-parametric models or highly flexible parametric distribution (e.g. GB2) are favored
- We seek to revive two historical traditions:
  1. Statistical equilibrium models $\Rightarrow$ underlying market processes
  2. Theory of labor market segmentation

We solve at least one problem in the labor market segmentation literature: sorting workers into segments exogenously!

The model

- Likelihood for a the K-component mixture model:

$$L[\Theta|\{x_i\}_n] = \prod_{i=1}^{N} \sum_{k=1}^{K} \lambda_k \, p_k \left[x_i|\theta_k\right] \tag{1}$$

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- Specifically: two-component exponential / log-normal mixture model:

$$p[x|\alpha, \mu, \sigma, \lambda] = \lambda \, \mathrm{Exp}[x|\beta] + (1-\lambda) \, \mathrm{lgN}[x|\mu, \sigma] \tag{2}$$

λ_k and p_k are the component weight and *pdf* respectively.

Model components

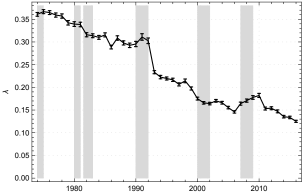
- Exponential: characterized by memoryless property
  - Part-time (less than 35 hrs. on average), low-wage (?) jobs
  - **Speculation:** frequently changing hours & approx. constant real wage
- Log normal: described by evolution of incomes à la Gibrat's law
  - Full-time (35+ hrs. on average)
  - **Speculation:** relatively constant hours & wage variation

Estimation

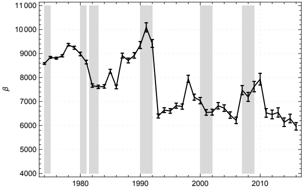
Data: Wage & salary data (WSAL_VAL) using weights (MARSUPWT)

- Both MLE & MCMC (Bayesian) estimation
  - Adjusted for censoring, since even the internal data is top-coded.
- Broad consideration of alternative models

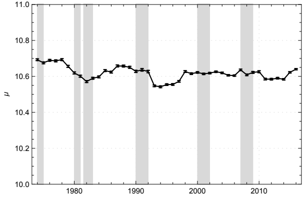
ML estimates



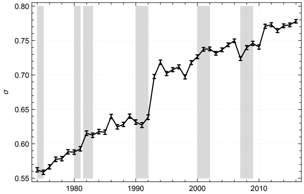
(a) Component Weight



(b) β (Exp)



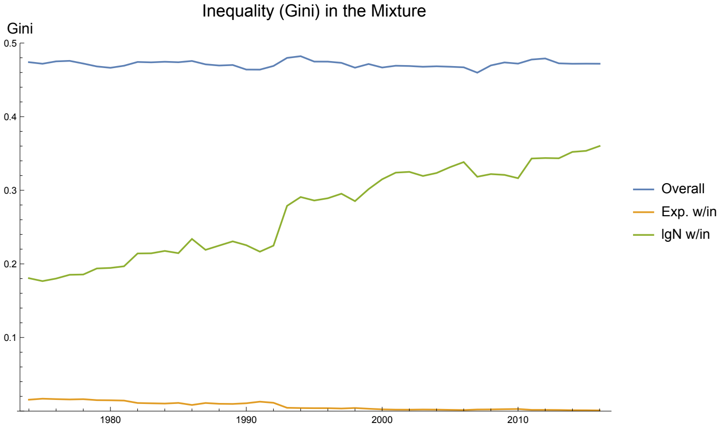
(c) μ (lgN, scale)



(d) σ (lgN, shape)

Scale parameters adjusted for inflation.

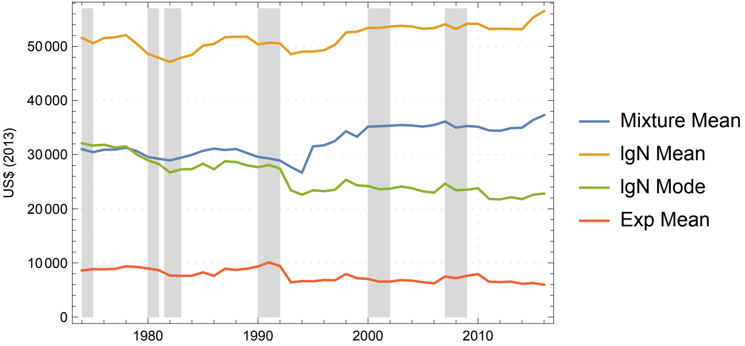
ML estimates: Inequality



Thank you!

ML estimates: Parameter Interpretations

Component	**Mean**	**Median**	**Mode**
Exponential	β	$\frac{1}{\ln 2}\,\beta$	0
Log-Normal	$\exp\left(\mu + \frac{1}{2}\,\sigma^2\right)$	$\exp\left(\mu\right)$	$\exp\left(\mu - \sigma^2\right)$



ML estimates: Inequality

Component	Mean	Gini
Exponential	β	0.5
Log-Normal	$\exp\left(\mu + \frac{1}{2}\sigma^2\right)$	$2\Phi(\sigma/2) - 1$

Gini decomposition:* $G = \sum p_i \cdot s_i \cdot G_{w_i} + (G_b + G_t)$

- G_{w_i}:
  1. Gini of exponential component is constant
  2. Gini of log-normal component is *increasing*
  3. Population & income shares of log-normal component *increases*
- G_b: between-component inequality
- G_t: Transvariation (overlap) between components ...

* p_i is the population share, s_i the income share captured in component i

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$\Rightarrow$ G_b, G_t not calculated separately $\Leftarrow$

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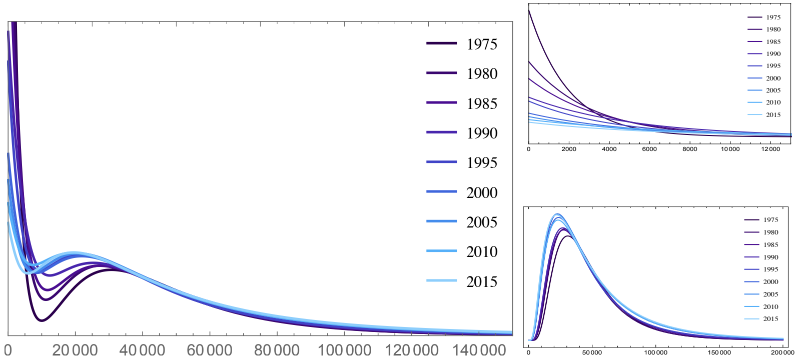
Model results

The model with inflation adjusted location parameters.



Three traditions

Camilo Dagum (1977) contrasted three approaches for finding a functional description of the income distribution.

1. Based only on Goodness-of-fit
2. Based on the generation of an income distribution by means of a stochastic process
3. Based on the solutions to differential equations that capture the regularity & permanence observed

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Failure to consider mixture models with a finite number of components $\Rightarrow$ Approach 1!

Further Work

- Theoretical Model
- Incorporating power-law tail (Pareto component)
- Refining *who* (type of worker, demographic) is captured in each component (with latent variables)
  - Implication for labor market segmentation & stratification
- Solving the mystery:
  Why is the exponential component apparently shrinking over the past 40 years?