Explaining Job Polarization in Europe: The Roles of Technology and Offshoring

Maarten Goos  
University of Leuven

Alan Manning  
London School of Economics

Anna Salomons  
Utrecht University School of Economics
Job polarization in Europe

Figure 2. European-Wide Polarization, 1993-2006

Note: Employment pooled across countries. 1993-2006 long difference: employment shares for 1993 and/or 2006 imputed on the basis of average annual growth rates for countries with shorter data spans.
# Job polarization by occupation group

<table>
<thead>
<tr>
<th>Occupation group</th>
<th>Employment share change</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Low-paying:</strong> Laborers + (elementary) service occupations</td>
<td>1.58</td>
</tr>
<tr>
<td><strong>Middling:</strong> Production, craft + office / clerical support occ’s</td>
<td>-7.77</td>
</tr>
<tr>
<td><strong>High-paying:</strong> Professional &amp; associate professional occ’s</td>
<td>6.19</td>
</tr>
</tbody>
</table>

Notes: Employment share changes are long differences for the period 1993-2006 and averaged across our sample of 16 EU countries. Occupations are ordered by their mean wage rank in 1993 across the 16 European countries. The occupations are grouped into the 4 lowest-paid, 8 middling and 9 highest-paid occupation groups.
Pervasiveness of job polarization
The canonical model

- Labor of different skill types (L and H) combined to produce one final good (Y) according to a CES production function:

\[ Y_t = \left[ \left( A_{L_t} L_t \right)^{\sigma^{-1}} + \left( A_{H_t} H_t \right)^{\sigma^{-1}} \right]^{\sigma \sigma^{-1}} \text{ with } \sigma \geq 1 \]

- Technological progress is skill-biased ("SBTC hypothesis"), leading to an increasing demand for high-educated labor

- Assuming competitive factor markets & perfectly inelastic relative supply, can empirically estimate key structural parameter, elasticity of substitution between high- & low-skilled workers (\(\sigma\))
The canonical model

- **Conditional labor demand framework**, justified by *shift-share analysis*: decomposing the change over time in the employment share of skill group *j* within and between industries *i*:

\[
\Delta s_j = \sum_i s_{i,t} \left[ s_{j|i,t} - s_{j|i,t-1} \right] + \sum_i s_{j|i,t-1} \left[ s_{i,t} - s_{i,t-1} \right]
\]

- Change in the skill group composition **within industries**.
- Change in the relative importance of skill group *j* **between industries**.

- Large part of **skill-upgrading was found to take place within industries** (Katz & Murphy (92), Bound & Johnson (92), Berman, Bound & Griliches (93)).
Rethinking the canonical model

This paper is based on **two main modifications** of the canonical model:

1. **The nature of technology:** task- rather than skill-biased

2. **Unconditional** rather than conditional **labor demand**

→ Both modifications together will allow us to better understand the phenomenon of job polarization
Rethinking the canonical model

This paper is based on **two main modifications** of the canonical model:

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Rethinking the canonical model: the nature of technology

- More nuanced view on technological progress proposed by Autor, Levy and Murnane (2003): **task-biased** technological progress
  
- **Routine tasks** are codifiable and **can be automated**; non-routine tasks cannot be automated
  - Routine tasks follow a set protocol
  - Non-routine tasks require mental flexibility or physical adaptability

- Examples..
## Routine and non-routine occupations

<table>
<thead>
<tr>
<th>Task</th>
<th>Task description</th>
<th>Example occupations</th>
<th>Computer impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Routine</td>
<td>Cognitive</td>
<td>Bookkeepers</td>
<td>Direct substitution</td>
</tr>
<tr>
<td>Routine</td>
<td>Manual</td>
<td>Assembly line workers</td>
<td>Direct substitution</td>
</tr>
<tr>
<td>Non-routine</td>
<td>Cognitive</td>
<td>Lawyers, scientists</td>
<td>Complementarity</td>
</tr>
<tr>
<td>Non-routine</td>
<td>Manual</td>
<td>Janitors, truck drivers</td>
<td>Limited substitution or complementarity</td>
</tr>
</tbody>
</table>
Rethinking the canonical model: the nature of technology

- Similarly, "trade in tasks": some tasks can be offshored whereas others cannot (Blinder (06), Grossman & Rossi-Hansberg (08)).

- Routine and offshorable tasks are located in the middle of the wage distribution (Goos & Manning (03, 07), Spitz-Oener (06), Goos, Manning & Salomons (09), Firpo, Fortin & Lemieux (11)): potential explanation for job polarization.

- This paper contributes to a growing literature on the labor market impacts of task-biased technological progress and task-offshoring (Autor & Dorn (10), Costinot & Vogel (10), Autor & Acemoglu (11), Firpo, Fortin & Lemieux (11), Autor, Hanson & Dorn (12,13))
Rethinking the canonical model

This paper is based on two main modifications of the canonical model:

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Rethinking the canonical model: unconditional labor demand

- Conditional labor demand approach assumes industry output mix unaffected by technological progress

- But industries use occupational tasks in different intensities: likely to lead to a between-industry effect of task-biased technological progress & offshoring

→ Examine shift-share analysis of occupational employment shares
A shift-share analysis of occupations

<table>
<thead>
<tr>
<th>Occupation group</th>
<th>Within industries</th>
<th>Between industries</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low-paying</td>
<td>0.77</td>
<td>0.76</td>
</tr>
<tr>
<td>Middling</td>
<td>-4.97</td>
<td>-2.78</td>
</tr>
<tr>
<td>High-paying</td>
<td>4.20</td>
<td>2.03</td>
</tr>
</tbody>
</table>

Notes: Averaged across all 16 countries. All numbers are percentage point changes in occupational employment shares over the 1993-2006 long difference where employment shares in 1993 and 2006 are imputed on the basis of average annual growth rates for countries with shorter data spans.
Agenda

1. A structural labor demand model capturing the impacts of task-biased technological change and task-offshoring

2. Extent to which the model can explain long-run job polarization in Europe

3. Job polarization in the Great Recession
### A task model of labor demand

<table>
<thead>
<tr>
<th>GOODS $i=1, \ldots, I$</th>
<th>$Y_i(T_i, \ldots, T_l) \rightarrow C_i^l = Y_i c_i^l (c_1^T, \ldots, c_j^T, \ldots, c_J^T)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i=1$</td>
<td>$T_{ij}</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TASKS $j = 1, \ldots, J$</th>
<th>$T_{ij} (N_{ij}, K_{ij}) \rightarrow C_j^T = T_{ij} c_j^T (w_j, r_j)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$j=1$</td>
<td>$N_{ij}</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>LABOR FROM OCCUPATION $j=1$</th>
<th>OTHER INPUT (CAPITAL, FOREIGN LABOR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_{ij}</td>
<td>Y_i = Y_i t_{ij} (c_1^T, \ldots, c_j^T, \ldots, c_J^T) n_j (w_j, r_j)$</td>
</tr>
<tr>
<td>$N_{ij} = Y_i (Y, P_i (c_i^l) / P) t_{ij} (c_1^T, \ldots, c_j^T, \ldots, c_J^T) n_j (w_j, r_j)$</td>
<td></td>
</tr>
</tbody>
</table>
Effects of TBTC and offshoring

Task-biased technical progress (TBTC) and task-offshoring are relative decreases in the price of “other inputs” in production of routine and offshorable tasks respectively.

Impacts of $r_j \downarrow$ on the demand for labor from routine / offshorable occupations:

1. Displacement effect within industries in the elasticity of substitution between inputs in task production;
2. Attenuation effect within industries in the elasticity of substitution between tasks in goods production;
3. Displacement effect between industries in the elasticity of substitution between tasks in goods production;
4. Attenuation effect between industries in the elasticity of substitution between goods in consumption.

$$N_{ij} = Y_i(Y, P_i(c_i^I) / P) t_{ij}(c_i^T, .., c_j^T, .., c_J^T) n_j(w_j, r_j)$$
A summary of the model

- A **general framework** capturing the employment impacts of task-biased technological progress and task offshoring depending on key structural parameters.

- Relative employment in routine and offshorable occupations decreases if displacement effects dominate attenuation effects.

- Can **account for polarization** since routine and offshorable tasks are performed by medium-skill workers.
Empirical specification

- We had:

\[ N_{ij} = Y_i(\mathcal{Y}, P_i(c_i^I) / P)T_{ij}(c_1^T, .., c_j^T, .., c_J^T)n_j(w_j, r_j) \]

- Assume the following **goods production** technology:

\[ Y_i(T_{i1}, .., T_{ij}) = \left[ \sum_{j=1}^{J} \left[ \beta_{ij}T_{ij} \right]^\frac{\eta-1}{\eta} \right]^\frac{\eta}{\eta-1} \text{ with } \eta > 0 \]

- Assume the following **task production** technology:

\[ T_{ij}(N_{ij}, K_{ij}) = N_{ij}^\kappa K_{ij}^{1-\kappa} \text{ with } 0 < \kappa < 1 \]

- Assume that preferences are homothetic and **product demand is iso-elastic** with \( \varepsilon > 0 \)
Structural labor demand equation

- Log linearization gives:

\[
\log N_{ij} = \log r_j - \log w_j
\]

\[
= \log c_j^T
\]

\[
= \eta \left[(1 - \kappa) \log r_j + \kappa \log w_j\right] + \eta \log c_i^l (c_1^T, \ldots, c_j^T, \ldots, c_J^T) + \beta_{ij}
\]

\[
+ \log L + \log \left(\frac{Y}{L}\right) - \varepsilon \log \left(\frac{P_i(c_i^l (c_1^T, \ldots, c_j^T, \ldots, c_J^T))}{P}\right)
\]
**Structural labor demand equation: data**

- **Labor demand equation (adding country-year subscripts):**

\[
\log N_{ijct} = -\left[ (1 - \kappa) + \eta \kappa \right] \log w_{ijct} + \left[ 1 - \eta \right] (1 - \kappa) \log r_{jt} + \eta \log c^I_{ict} + \beta_{ijc} + \log L_{ct} + \log \left( \frac{Y_{ct}}{L_{ct}} \right) - \varepsilon \log \left( \frac{P_{ict}}{P} \right)
\]

- **hours worked (ELFS)**
- **hourly wages (EHCP, EU-SILC, UKLFS, OECD)**
- **coefficient*routine*tt; or coefficient*offshorability* tt**
- **industry marginal costs (STAN)**
- **industry-occupation-country fixed effect**
- **population (STAN)**
- **income/capita (STAN)**
- **price index (STAN)**
Measuring technological progress and offshoring at the task level

- **Occupation specific measures of:**
  - Routine Task Intensity \((RTI_j)\) from Autor, Levy & Murnane (03), based on Dictionary of Occupational Titles (DOT) data.
  - Offshorability index \((OFF_j)\) from the European Restructuring Monitor (ERM).

- Occupation specific measures are interacted with a **time-trend** to capture task-biased technological change and task-offshoring respectively (e.g. \(RTI_j \times \text{time-trend}\)).
Structural labor demand equation: estimating parameters

- Labor demand equation:

\[
\log N_{ijct} = -\left[ (1 - \kappa) + \eta \kappa \right] \log w_{ijct} + [1 - \eta] (1 - \kappa) \log r_{jt} + \eta \log c^I_{ict} + \beta_{ijc} + \log L_{ct} + \log \left( \frac{Y_{ct}}{L_{ct}} \right) - \varepsilon \log \left( \frac{P_{ict}}{P} \right)
\]

- Hours worked (ELFS)
- Hourly wages (EHCP, EU-SILC, UKLFS, OECD)
- Industry marginal costs (STAN)
- Industry-occupation-country fixed effect
- Population (STAN)
- Income/capita (STAN)
- Price index (STAN)
## Estimates of structural parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate (clustered std error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trend(Routine)</td>
<td>-0.92* (0.21)</td>
</tr>
<tr>
<td>Trend(Offshoring)</td>
<td>-0.41* (0.20)</td>
</tr>
<tr>
<td>Elasticity of substitution between tasks in goods production</td>
<td>0.85* (0.15)</td>
</tr>
<tr>
<td>Elasticity of substitution between goods in consumption</td>
<td>0.31* (0.13)</td>
</tr>
</tbody>
</table>
Predicted labor demand changes due to technological progress and offshoring

- Differentiating with respect to a change over time in $r_{jt}$ all else constant gives:

$$\frac{\partial \log N_{ijct}}{\partial t} = \left[1 - \kappa\right] \frac{\partial \log r_{jt}}{\partial t}$$

Displacement

$$-\eta \left[1 - \kappa\right] \frac{\partial \log r_{jt}}{\partial t}$$

Attenuation

$$+\eta \frac{\partial \log c_{ict}^l}{\partial \log r_{jt}} \frac{\partial \log r_{jt}}{\partial t}$$

Displacement

$$-\epsilon \frac{\partial \log c_{ict}^l}{\partial \log r_{jt}} \frac{\partial \log r_{jt}}{\partial t}$$

Attenuation

Within industry polarization if $1 > \eta$

$(\eta = 0.85)$

Between industry polarization if $\eta > \epsilon$

$(\epsilon = 0.31)$
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### Actual and predicted job polarization

<table>
<thead>
<tr>
<th>Occupation group</th>
<th>Actual employment share change</th>
<th>Predicted employment share change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low-paying</td>
<td>1.58</td>
<td>2.26</td>
</tr>
<tr>
<td>Middling</td>
<td>-7.77</td>
<td>-8.34</td>
</tr>
<tr>
<td>High-paying</td>
<td>6.19</td>
<td>6.13</td>
</tr>
</tbody>
</table>

Notes: Employment share changes are long differences for the period 1993-2006 and averaged across our sample of 16 EU countries. Results are pervasive across our sample of countries.
Job polarization within and between industries

<table>
<thead>
<tr>
<th>Occupation group</th>
<th>Within industries</th>
<th>Between industries</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual</td>
<td>Predicted</td>
</tr>
<tr>
<td>Low-paying</td>
<td>0.77</td>
<td>0.22</td>
</tr>
<tr>
<td>Middling</td>
<td>-4.97</td>
<td>-4.84</td>
</tr>
<tr>
<td>High-paying</td>
<td>4.20</td>
<td>4.70</td>
</tr>
</tbody>
</table>

Notes: Averaged across all 16 countries, all changes in percentage points.
## Between industry effects

<table>
<thead>
<tr>
<th>Occupation group</th>
<th>Predicted between industry change</th>
<th>Displacement effects</th>
<th>Attenuation effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low-paying</td>
<td>2.04</td>
<td>3.18</td>
<td>-1.13</td>
</tr>
<tr>
<td>Middling</td>
<td>-3.50</td>
<td>-5.44</td>
<td>1.94</td>
</tr>
<tr>
<td>High-paying</td>
<td>1.43</td>
<td>2.22</td>
<td>-0.79</td>
</tr>
</tbody>
</table>

Notes: The first column gives the predicted employment share. The second column gives the predicted changes conditional on industry output. The third column gives the predicted changes due to consequent changes in relative industry output prices.
# Technology and offshoring

<table>
<thead>
<tr>
<th>Occupation group</th>
<th>Total predicted changes</th>
<th>Changes due to technology</th>
<th>Changes due to offshoring</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low-paying</td>
<td>2.26</td>
<td>0.90</td>
<td>1.37</td>
</tr>
<tr>
<td>Middling</td>
<td>-8.34</td>
<td>-5.48</td>
<td>-2.86</td>
</tr>
<tr>
<td>High-paying</td>
<td>6.13</td>
<td>4.63</td>
<td>1.50</td>
</tr>
</tbody>
</table>

Notes: The first column gives the predicted employment share changes. The second column gives the predicted changes only accounting for task-biased technological change. The third column gives the predicted changes only accounting for task offshoring.
Extension I: The nature of technological progress

- Task-biased technological progress can be due to:
  - A decrease in price of capital **displacing (domestic) labor** in routine task production – as in other recent task models (e.g. Autor, Levy and Murnane (03), Grossman & Rossi-Hansberg (08), Autor & Dorn (10), Acemoglu & Autor (11)).
  - An relative increase in (domestic) **labor augmenting productivity** of non-routine occupations – in the spirit of the canonical framework & growth models.

- We find that the majority of job polarization is due to **displacement of (domestic) labor** in routine task production by capital.
Extension II: Non-homothetic preferences

- For now, we assumed homothetic preferences in product demand- but non-homothetic preferences may also cause changes in the employment structure.

- These effects can be included in our model: we empirically identify the changes in the industry composition of consumption due to changes in income per capita or in income inequality.

- We find only small effects on the employment structure.
Conclusions: Explaining long-run job polarization

- **Canonical model** of the labor market cannot account for pervasive job polarization, both within & between industries

- We provide an **empirically identifiable task-based framework** to model **technological progress** and **offshoring** accounting for within and between industry effects on the structure of occupational employment.

- **Task-biased technological change** and **task-offshoring** can explain job polarization in Europe

- Important to consider effects on **unconditional labor demand**
Agenda

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Shares of Hours Worked by Occupation Group Yearly, 1993-2010, 1993=100

Note: Data are taken from the European Labour Force Survey.
Employment Shares by Occupation Group Quarterly, 2006Q1-2012Q3, 2006Q1=100

Note: Data are taken from Eurostat's Online Statistical Database.
Total Employment Quarterly, 2006Q1-2012Q3, 2006Q1=100

Note: Data are taken from Eurostat's Online Statistical Database.
Total Employment by Occupation Group Quarterly, 2006Q1-2012Q3, 2006Q1=100

Note: Data are taken from Eurostat's Online Statistical Database.
Conclusion: Job polarization in the Great Recession

- Employment structure changes in Europe are continuing between 2006-2012

- Developments are stronger during the Great Recession:
  - Adjustment by job destruction rather than differential job growth
  - Not clear that lost Routine jobs will be recovered in the short run

- Highlights the importance of further research into worker-level outcomes (earnings, unemployment) and the absorption of shocks in local economies