

Welfare Costs of Occupational Decline: Counterfactual Approach

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- McKinsey (2017): by 2030 3-14% of global workforce lose jobs to automation
- Brynjolfsson et al (2018): 9% of workers in the US are at high risk of automation
- Large manufacturing job losses (and gains) in 2000's due to trade and offshoring
- Is it a big deal?
- Should we have TAA analogue for jobs lost to automation?

Where All the Breaker Boys Have Gone?



- **How large would be welfare costs of displaced workers?**
- Depends on skill contents and amenities of different jobs
- Problems:
 - We do not know how to classify skills/amenities in the best way
 - Typically no information on workers' skills and preferences
 - Not least: little historic data for still active occupations
- Solution: structural model of occupational choice with latent skills
- Allows to model heterogeneity of losses between workers and occupations

- The model with four latent workers characteristics explains 99% of variation in the occupational transitions probabilities
- Welfare losses vary significantly between occupations
 - Large losses for broadly classified occupations requiring specific skills/amenities (24% for professionals)
 - Much smaller losses for narrowly defined groups: around 7-12% for most occupations
- Previous results:
 - Edin et al (2018): workers in declining occupations lose 2-5% of earnings in the long run
 - Displaced workers lose between 7 to 25% of earnings in the long-run (Jacobson, LaLonde and Sullivan, 1993; Eliason and Storrie, 2006)

Model 1

- Time is discrete $t = 1, 2, ..T$
- Continuum of heterogeneous workers chooses between J occupations
- A worker p chooses an occupation C_{pt} maximizing their utility $C_{pt} = i, |U_{pi} \geq U_{pj}, \forall j \in 1, 2..J$
- Vector X_p of length d describes worker's p skills and preferences
- Vectors A_j^S and A_j^T describe job skill sensitivities and amenities respectively
- The cdf $F()$ describes the distribution of workers' characteristics

- Worker's p utility in occupation j includes monetary W_{pjt} and non-monetary benefits T_{pjt} :

$$U_{pjt} = \alpha W_{pjt} + T_{pjt}$$

- Monetary benefits (wage) depends on the the match between worker's characteristics and job skill sensitivities and on the idiosyncratic shock:

$$W_{pjt} = P_{jt} + X_p A_j^S + \eta_{pjt}, \eta_{pjt} \sim N(0, \sigma^2)$$

- Non-monetary benefits depend on the match and on the taste shock ϵ_{pjt} :

$$T_{pjt} = X_p A_j^T + \epsilon_{pjt}, \epsilon_{pjt} \sim EV(1)$$

- Indirect utility is $V_{pjt} \equiv W_{pjt} + X_p A_j^T$

Example

Occupations:

	A	B	C
<i>strength</i>	$\begin{bmatrix} 0 \\ 4 \end{bmatrix}$	$\begin{bmatrix} 1 \\ 3.5 \end{bmatrix}$	$\begin{bmatrix} 4 \\ 0 \end{bmatrix}$
<i>intelligence</i>			

For a person $X = [0.5, 1]$:

- $V_A = [0.5, 1] * [0, 4]' = 4$
- $V_B = [0.5, 1] * [1, 3.5]' = 4$
- $V_C = [0.5, 1] * [4, 0]' = 2$

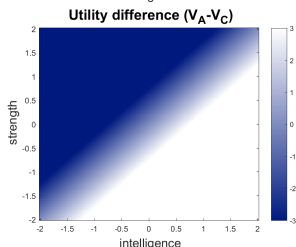
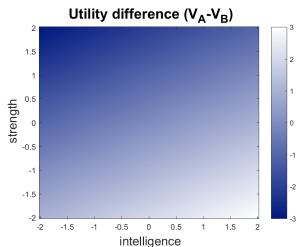
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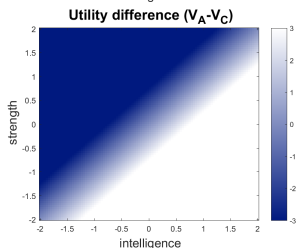
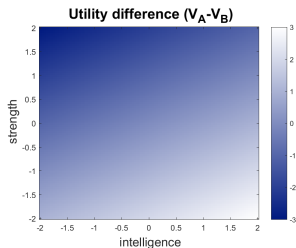
$$\begin{array}{l} \text{strength} \\ \text{intelligence} \end{array} \quad \begin{array}{c} \mathbf{A} \\ \left[\begin{array}{c} 0 \\ 4 \end{array} \right] \end{array} \quad \begin{array}{c} \mathbf{B} \\ \left[\begin{array}{c} 1 \\ 3.5 \end{array} \right] \end{array} \quad \begin{array}{c} \mathbf{C} \\ \left[\begin{array}{c} 4 \\ 0 \end{array} \right] \end{array}$$

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Occupational transitions:

	A	B	C
A	0.228	0.095	0.034
B	0.095	0.061	0.039
C	0.0343	0.039	0.375



- The probability that a worker p with characteristics X_p chooses an occupation j is:

$$P_j(X_p, \eta) = \frac{\exp(V_j(X, \eta))}{\sum_k \exp(V_k(X, \eta))}$$

- Proportion of workers choosing occupation i is:

$$P_i = E(P_i(X, \eta))$$

- Proportion of workers switching from occupation i to j is:

$$P_{ij} = E(P_i(X, \eta)P(j(X, \eta)))$$

Welfare Analysis

- What is the effect of the decline in occupation j on the welfare of workers?
 - Workers within an occupation j lose jobs
 - Workers in other occupations lose the opportunity to switch to jobs in j

- Welfare costs of all the workers account for both effect:

$$EC_j = (1/\alpha)(E[U] - E[U_{-j}])$$

- Welfare costs of workers within an occupation j account for the strongest first effect:

$$EC_{ij} = (1/\alpha)(E[U|U_{it} \geq U_{kt}] - E[U_{-j}|U_{it} \geq U_{kt}])$$

- Use the simulated method of moments (SMM)
- Draw S random vectors of skills from the normal skill distr.
 $X \sim N(0, I)$
- \rightarrow Estimate moments $P_{ij} \rightarrow \hat{P}_{ij}$:

$$\hat{P}_{ij} = \frac{1}{S} \sum_{p=1}^S \frac{\exp(A_i X_p') \exp(A_j X_p')}{(\sum_{k=1}^J \exp(A_k X_p'))^2}$$

- Matching to the frequencies of occupational transitions observed in the data
- Gradient of the objective function has an analytic form (too cumbersome to write it here)

Identification

- Good news: occupational transitions identify both welfare costs up to scale with $T \rightarrow \infty$:

- Both measures can be written as an infinite sum of data moments:

$$EC_j = \sum_{n=1}^{\infty} \frac{1}{\alpha n!} E[P_j(X, \eta)^n]$$

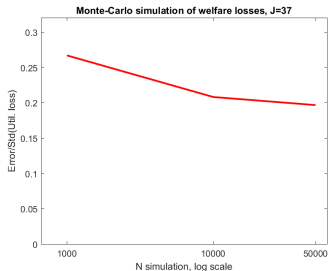
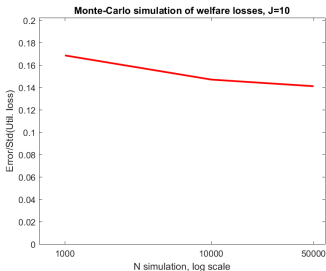
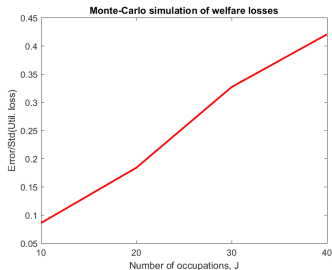
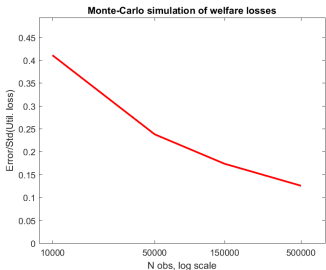
$$EC_{ij} = \sum_{n=1}^{\infty} \frac{1}{\alpha P_i n!} E[P_i(X, \eta) P_j(X, \eta)^n]$$

- Partial sums are within 10% of value for $T = 2$.
- Bad news: no identification for A (without wage data)
 - Any rotation of A does not affect the moments (occupational transitions matrix).
 - Any permutation of rows of A does not affect the moments

Monte-Carlo Analysis

- 1 Does the SMM approach produces consistent estimates of welfare costs?
 - How does the bias and the standard deviation of estimates changes with then number of observations N ?
- 2 How many simulation draws S is necessary for "good" estimates?
- 3 How does the error change with the number of occupations J ?
 - Algorithm:
 - 1 Pick one random seed
 - 2 Generate data (X_0, A_0, ϵ) with different N (S, J) observations
 - 3 Simulate S draws of X

Monte-Carlo Analysis: Welfare Loss Estimation Error



Monte-Carlo Analysis: Estimation Example

- Measure welfare losses of workers in each occupation from making an occupation obsolete.

Occupation	Actual loss(perc.)	Predicted loss(perc.)
1	31.36	29.00
2	38.97	37.75
3	34.39	31.37
4	25.67	29.36
5	28.89	29.94
6	30.42	31.06
7	31.76	34.93
8	25.63	28.43
9	46.25	37.99
10	28.49	32.41

- Good approximation of welfare losses: $R^2=0.999$ for magnitude, $R^2=0.67$ for percentage losses

- Use linked March CPS data 2008-2018, age > 25
- → Each worker is observed for two consecutive years
- Use only the workers employed full-time in both years and workers out of labor force (home sector)
- Use two-digit occupational code and recode rare occupations into more general groups
- → End up with 37 occupations including the home sector
- Calculate the transition frequency for each pair of occupations

- Two results:
 - 10-occupations classification, $d = 2$, $S = 10000$
 - 37 occupations classification, $d = 4$, $S = 10000$
- Models' fit:

d	1	2	3	4
R^2	0.78	0.85	0.983	0.993

- The model explains 99% of variation in the occupational frequencies for $d = 4$ (overidentification test is rejected)
- Next, calculate counterfactual welfare losses by using estimated \hat{A} .

Aggregate Results: Welfare Losses by Occupation

- Top-10 occupations (out of 37) with largest potential welfare losses:

Occupation	Welfare loss(perc.)	St.error	Welfare loss	St. error
Home sector	24.70	5.47	-4.99	1.16
Professionals	23.50	4.63	-3.67	0.79
Clerical support workers	19.40	4.69	-2.62	1.13
Service and sales workers	18.27	5.41	-2.89	0.85
Technicians and associate professionals	18.09	3.36	-2.03	0.57
Crafts and related trades	17.83	4.05	-2.83	0.89
Plant and machine operators, assemblers	16.75	4.21	-2.83	1.06
Managers	15.79	3.69	-1.93	0.32
Elementary occupations	14.47	3.43	-1.98	0.46
Skilled agricultural, forestry and fishery	11.84	4.38	-1.25	0.67

- Amenities, education requirement, generality matter

Results: Welfare Losses by Occupation

- Top-10 occupations with the largest potential welfare losses conditional on becoming obsolete

Occupation	Welfare loss(perc.)	Welfare loss
Teachers	21.06	-6.06
Home sector	19.72	-4.76
Lawyers	15.69	-3.27
Office and Administrative Support	15.10	-2.04
Other healthcare practitioners and technical –	14.86	-3.12
Installation, Maintenance, and Repair	13.82	-3.14
Construction and Extraction	13.66	-4.01
Drivers and transportation workers	13.18	-2.87
Personal Care and Service	11.74	-2.30
Maintenance occupations	11.39	-2.59

Comparing to Previous Results

- My estimation predicts welfare losses of 5-25%
- Workers in most occupations lose from 7 to 12%
- Wide range of estimates of wage losses in the literature due to layoffs (4-50%):
 - Jacobson, LaLonde, Sullivan (1993): displaced workers lose about 25% of wages per year five years after the layoff
- Layoffs are different from gradual declines:
 - Edin, Evans, Graetz, Hernnas and Michaels (2018): workers in declining industries lose around 5% in earnings
- Previous estimates do not account for amenities.

Previous Results on Skill Transferability

- No fully structural approach for skills/amenities transferability
- Switching costs=ad-hoc function of task contents of occupations:
 - Gattman and Schonberg (2010), Cortes and Gallipoli (2014), Gibbons(2016)
- Switching costs=ad-hoc function of occupational transition probability: Shaw (1984,1987)
- Contribution: measure transferability for both skills and preferences, no ad-hoc assumptions on skills and their scaling

Conclusion and Future Work

- Develop a new approach to predict welfare cost of occupational decline
- Welfare costs > earnings costs in the literature
- Losses are highly heterogeneous (between occupations and workers)
- Workers in most occupations lose from 6 to 10%
- Next: incorporate wage data; contrast estimates with O-NET data