Welfare Costs of Occupational Decline: Counterfactual Approach

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Summary

I describe a novel minimal approach to measure counterfactual welfare costs of occupational decline due to automation, trade policy or government regulation. In contrast to previous studies, this approach accounts for both monetary and non-monetary costs of displaced workers. It relies on a multi-sector Roy (1951) model of occupational choice with multiple latent worker's characteristics, which describe both workers' skills and preferences. Identification of welfare costs comes fro the panel data on occupational transitions and wages. My preliminary estimation results on the linked March CPS data show that welfare costs of occupational decline depend vary from 2% to around 20% of welfare depending on occupation. For most two-digit occupations losses lie in the range from 7 to 12%. The losses become higher if an occupational decline affects a larger group such as a one-digit occupation. My estimates exceed the measured earnings losses of workers experiencing an occupational decline (Edin et al, 2018).

Motivation

- By 2030 between 3 and 14 percent of global workforce will have to switch occupations due to automation (McKinsey, 2017).
- Brynjolfsson et al (2018): 9% of workers in the US are at high risk of automation
- Is it a big problem? Do we need to compensate displaced workers and if so, then how much?

Research Question

- **How large are welfare losses of displaced workers in still existing occupations?**
- Challenges:
  - No or little historic data to evaluate losses
  - Usually no information on workers' skills and preferences
- Previous results point to significant earnings losses for displaced workers:
  - 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

- Roy model with M sectors/occupations and continuum of heterogeneous workers
- Each period $t = 1, 2 ... T$ workers choose occupations to maximize utility
- Vectors A^S_j and A^T_j with $J \times (k+1)$ dimensions describe occupation j technology and amenities
- Vector X_p of length k describes skills and preferences of worker p
- The utility of worker p in occupation j:

$$U_{pjt} = \alpha W_{pjt} + T_{pjt} = \alpha(P_{jt} + X_p A^S_j + \eta_{pjt}) + X_p A^T_j + \epsilon_{pjt}$$

- $V_{pjt} \equiv \alpha(P_{jt} + X_p A^S_j + \eta_{pjt}) + X_p A^T_j$ - indirect utility (sans taste shocks)
- CDF $F()$ describes the distribution of worker's characteristics X

P_{jt} - skill price η_{pjt} -wage shock, $\epsilon_{pjt} \sim EV(1)$ - taste shock, α - utility of income

- Conditional on X and η choice probabilities are standard for multinomial logit model:

$$P_i(X, \eta) = \frac{\exp(V_i(X, \eta))}{\sum_k \exp(V_k(X, \eta))}$$

- Unconditional probabilities:

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

- The model generates testable predictions on occupational transition probabilities P_{ij}:
  - Symmetry of transition probabilities: $P_{ij} = P_{ji}, \forall i, j$
  - "Triangle inequality": $P_{ij} \geq P_{ikj}, \forall i, j, k$

Welfare Losses

We want to measure annualized monetary compensation which makes workers indifferent between the default world and the world without occupation j:

- Change in expected utility losses of all workers from removing occupation j:

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

- Expected utility losses of workers in occupation i from removing occupation j:

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

Estimation and Identification

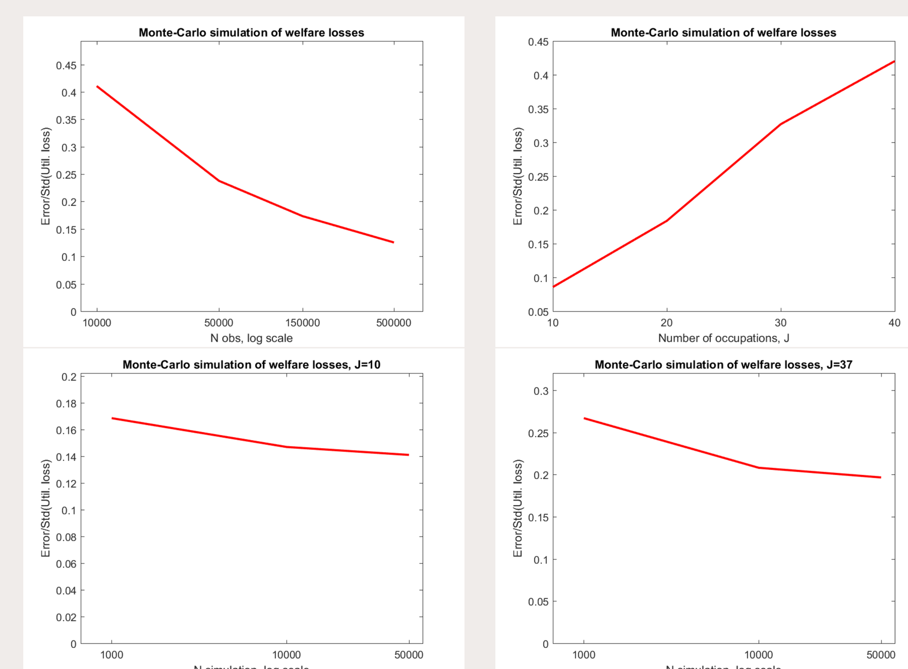
- **Workers' characteristics X and wage shocks are latent!**
- Use the simulated method of moments to estimate the model:
  - Goal: match frequencies of occupational transitions
  - Additionally: use simulated maximum likelihood to account for wages
- Assuming $T \to \infty \implies$ non-parametric identification of welfare losses up to scale
  - Observed occupational transitions identify both welfare measures (up to scale α):

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

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

  - Technically it requires a long history of occupational transitions T
  - In practice, the first two elements in the sum ($T = 2$) approximate the welfare costs very closely
  - No assumptions on skills distributions, does not require the data on skills, preferences or job characteristics...
- Use parametric estimation both to find welfare losses and to test the model

Monte-Carlo Simulation



- Random characteristics of J jobs A and N workers' X_0, $N \times T$ shocks $\epsilon \implies$ occupation histories and welfare costs
- $X \sim N(0, I)$ (equivalent to any multivariate normal)
- Estimate $\hat{A}$ with S simulations of X_S
- Calculate estimated welfare losses (based on $\hat{A}$ and X_S) and contrast with actual losses (based on A and X_0)
- Produces unbiased estimates of welfare costs of occupational decline
- Acceptable accuracy (<50% st. dev.) for samples of practical size (¡100,000 obs), but lower accuracy for larger N of occupations (J)
- More accurate results when incorporating wage data with SML (not reported)

Data

- Use linked March CPS data 2008-2018, age>25
- $\to$ Each individual is observed for two consecutive years
- Use only the individuals present in both years
- Recode into 37 occupations including the home sector

Model's Fit

- We can choose a number of latent worker's characteristics d to better fit the data

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

- The model with 4 latent skills ($d = 4$) explains 99% of variation in the occupational frequencies

Welfare Losses

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 Occupations	15.10	-2.04
Other healthcare practitioners and technical workers	14.86	-3.12
Installation, Maintenance, and Repair Occupations	13.82	-3.14
Construction and Extraction Occupations	13.66	-4.01
Drivers and transportation workers	13.18	-2.87
Personal Care and Service Occupations:	11.74	-2.30
Maintenance occupations	11.39	-2.59

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