

# *Occupational Switching and Self-Discovery in the Labor Market*

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## What is it about?

Study the implications for lifetime earnings and mobility of *mismatch* between a worker's skills and her/his occupation

1. Empirically: develop a new measure of mismatch
  - ▶ Effect of mismatch on occupational mobility
  - ▶ Effect of (current and past) mismatch on wages
2. Structurally: construct a quantitative model to assess the importance of occupational learning for earnings (growth, dispersion, etc.)

### Findings:

Empirical analysis suggests that occupational mismatch matters a lot  
Computations are still preliminary but suggest this is borne out by the model

# *I. Empirical analysis*

## *Data and measurement*

- ▶ Novelty is to combine O\*NET with a new source of information: ASVAB scores [ASVAB score: workers' endowment in a set of occupational-relevant skills]
- ▶ Data: NLSY79, organized into an annual panel spanning years 1979 to 2010 [careful work in defining employment spells and using consistent classifications]
- ▶ Skill portfolios: worker  $i$  has skills  $(s_i^1, \dots, s_i^J)$  and occupation  $k$  has requirements  $(r_k^1, \dots, r_k^J)$ ; Operationalize mismatch has the distance between  $\vec{s}_i$  and  $\vec{r}_k$

## Regression results

	(1)	(2)	(3)	(4)
Cumul mismatch	-0.061** (0.024)		-0.037 (0.024)	-0.190*** (0.025)
Mismatch $\times$ Occ tenure		-0.017*** (0.004)	-0.018*** (0.006)	-0.014** (0.006)
Mismatch		-0.032 (0.028)	-0.010 (0.035)	-0.004 (0.034)

- ▶ Mismatch in the current occupation is non-significant while the interaction with occupational tenure is negative and significant
- ▶ Comparison with OLS: mismatch is significant, interaction is  $\simeq$  zero
  - ▶ Difference with IV is consistent with unobserved match quality
  - ▶ Would be interesting to show OLS with your own match-quality variable

## *Remarks about the empirical analysis*

- ▶ How to deal with O\*NET scores that are differently related in absolute values to ASVAB scores?
- ▶ How should we think of occupational tenure when we also measure cumulative mismatch or cumulative match quality?
- ▶ Can you use the data to rule out other sources of wage growth?  
Lower wage in the past → weak bargaining position → lower wage today

## *II. Quantitative model*

## Model: key ingredients

### Demand side:

- ▶ Occupation  $\equiv$  a bundle  $(k_1, k_2)$  that produces an intermediary good
- ▶ Competitive firm aggregates  $y(k_1, k_2)$  into the final good
- ▶ Can work out the price of input in each occupation i.e.  $P(k_1, k_2)$

### Supply side:

- ▶ Ben-Porath model with uncertainty: investment and learning about skill level  $A_i$ :

$$h_{i,t+1} = (1 - \delta)h_{i,t} + q_{i,t} ; C(q_{i,t}, A_i, \varepsilon_{i,t}) = c(q_{i,t})e^{-(A_i + \varepsilon_{i,t})} ; \tilde{A}_i = A_i + \varepsilon_{i,t}$$

- ▶ Each period, form expectations about  $A_i$  using current estimate  $\hat{A}_i$ ,  $i = 1, 2$
- ▶ Worker's state at time  $t$ :

$$h = (h_1, h_2) ; \hat{A} = (\hat{A}_1, \hat{A}_2) ; \sigma_A^2$$

## Model: learning

- ▶ Initial beliefs are normally distributed with precision  $\phi_a = 1/\sigma_{A,0}^2$
- ▶ The noise term is also normally distributed, with precision  $\phi_\varepsilon = 1/\sigma_\varepsilon^2$

### Learning is tractable at the individual level:

- ▶  $t$  is a sufficient statistic for cumulative precision of beliefs  $\phi_t = \phi_a + t\phi_\varepsilon$   
[no need to carry  $\sigma_{A,t}^2$  as a state variable]
- ▶ Update is a precision-weighted average

$$\hat{A}' = \frac{\phi_t}{\phi_{t+1}} \hat{A} + \frac{\phi_\varepsilon}{\phi_{t+1}} \tilde{A}$$

### Learning is tractable when aggregated across agents

- ▶ Need to keep track of beliefs in each cohort; Normally distributed around true mean and precision  $t\phi_\varepsilon$
- ▶ Also straightforward to aggregate across cohorts  
[simplifies the computation of the time-invariant distribution]

## *Remarks about the model: learning*

Tractability is a nice feature; some remarks about the underlying assumptions:

- ▶ Bayesian learning converges quickly; this may go against your story  
[recall: weight of the most recent observation is  $\frac{\phi_\varepsilon}{\phi_{t+1}}$ ]
- ▶ The noise term is multiplicative: the costs of acquiring skills are larger for high-requirements occupations
- ▶ Uncertainty is actually beneficial: makes workers accumulate too much human capital, and this eventually raises output and wages

## *Remarks about the model: relationship to the data*

- ▶ Mapping between the model and motivating facts on occupational mobility
  - ▶ Mismatch is fine, but how to measure occupational tenure in the model?
  - ▶ Bayesian learning  $\Rightarrow$  mobility falls quickly with age  
Less investment towards the end of the lifecycle  $\Rightarrow$  more mobility
- ▶ Explain why certain mechanisms are needed to explain the data
  - ▶ Complementarity of  $k_1$  and  $k_2$  in production function  $y(\cdot)$ ?
  - ▶ Intuition would also help explain how  $\rho$  and  $\mu$  are calibrated
- ▶ Would be interesting to have skills that differ with respect to uncertainty:  
Predict the price of brain vs. Predict the cost of maintaining brawn

## *Remarks about the model: what are the next steps?*

- ▶ This could be a paper about the sources of lifetime earnings inequality
  - ▶ Uncertainty during the learning process ( $\sigma_\varepsilon$ ) vs. Uncertainty before entering the labor market ( $\sigma_{A,0}$ )
  - ▶ [Huggett, Ventura & Yaron [AER '11] find that  $\sigma_{A,0}$  matters enormously]
- ▶ This could be a paper about changes in the U.S. wage distribution
  - ▶ Uncertainty in the model creates a wage premium (why would  $\sigma_\varepsilon$  have increased over time?)
  - ▶ Assess the role of general equilibrium effects for the spread in the wage distribution (compute the output loss from mismatch?)

## *Concluding remarks*

- ▶ The paper is interesting for those who work on occupational choices:
  - ▶ A new source of data, the ASVAB scores
  - ▶ Careful work on linking this to O\*NET data
- ▶ The quantitative model has the potential to address some substantive issues; looking forward to seeing the future applications of the model