STEM CAREERS AND TECHNOLOGICAL CHANGE

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- STEM majors:Science, Technology, Engineering, and Math.
  - Applied Science: computer science, engineering ...
  - Pure Science: biology, chemistry, physics, mathematics ...
- This paper argues that:
  1. the high initial returns for STEM
  2. exit from STEM careers over time

  have a common cause – ”technological change”, which introduces new job tasks and makes old ones obsolete.
- Several new facts about labor market returns for STEM majors:
  1. The earnings premium for STEM majors is highest at labor market entry, and declines by more than 50% in the first decade of working life. (for ”applied”, not for ”pure”)
  2. Flatter wage growth coincides with a relatively rapid exit of STEM majors from STEM occupations.
- This paper also shows that STEM jobs indeed have the highest rates of task change.

DATA AND EMPIRICAL RESULTS

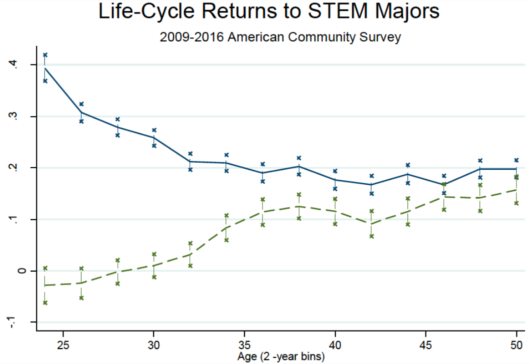
Two main data sources:

- ACS(2009 - 2016): American Community Surveys
  - has collected data on college majors since 2009
- NSCG (1993 - 2013): National Survey of College Graduates
- To estimate the pattern of Life-cycle returns to STEM, run the regression using the ACS data:

$$\ln(y_{it}) = \alpha_{it} + \sum_{a}^{A} \beta_a A_{it} + \sum_{a}^{A} \gamma_a (A_{it} * AS_{it}) + \sum_{a}^{A} \delta_a (A_{it} * PS_{it}) + \zeta X_{it} + \theta_t + \epsilon_{it} \tag{1}$$

- A_{it}: indicator function for age group.
- AS_{it} and PS_{it}: indicator functions for applied(pure) science majors.
- X_{it}: controls for race, ethnicity, years of completed education...
- θ_t: year fixed effect.

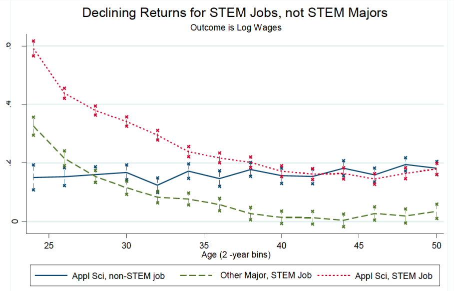
Results



- Each point is a γ or δ coefficient.
- Overall, applied science degree holders earn the highest wage premium at the beginning, but experience the flattest wage growth.

MAJORS OR OCCUPATIONS?

- Question: IS declining return in wage an inherent feature of STEM jobs, or is it something about the characteristics of students who choose to major in STEM?
- Estimate a version of equation (1) by adding interactions between age categories and indicators for being employed in a STEM occupation, as well as three-way interactions between age, an applied science major, and STEM occupation.
- Result



- Why do STEM careers have flatter wage earnings profile?
    - One possible reason: STEM careers have relatively higher replacement rate of tasks.
- Calculate change of task demand within each occupation using vacancy data from Burning Glass Technologies for the year 2007-2017.
- Measurement of the task change rate at the occupation level:

$$\text{TaskChange}_{0} = \frac{\sum_{t=1}^{T} \left\{ \text{Abs}\left[\left(\frac{\text{Task}_0^t}{\text{JobAds}_0}\right)_{2017} - \left(\frac{\text{Task}_0^t}{\text{JobAds}_0}\right)_{2007} \right] \right\}}{\sum_{t=1}^{T} \left\{ \left[\left(\frac{\text{Task}_0^t}{\text{JobAds}_0}\right)_{2017} + \left(\frac{\text{Task}_0^t}{\text{JobAds}_0}\right)_{2007} \right] \right\}}$$

- Results:
    - Overall, STEM jobs have a rate of task change that is about one standard deviation higher than all other occupations.

A stylized model of educational choice and learning (in school and on the job) that can account for the empirical patterns.

- Productions for firms:

$$Y_{jt} = \int_0^1 y_{jt}(i)di$$

  - Y_{jt}: unique final good for each industry j in each year t.
  - y_{jt}: production level of task i in occupation j at time t,

$$y_{jt} = \alpha_{jt} \times l_{jt}$$

    where α_{jt} is the productivity in each task, and l_{jt} is the total amount of labor supplied for each task.

MODEL SETUP - LABOR SUPPLY

- Workers maximize:

$$\max_{s,jt}\left\{\left[\sum_{t=0}^{T} PDV(W_{jt}(a,s,\alpha_{jt}))\right] - C(a,u,s)\right\}$$

  - a: ability; u: taste parameter; $s \in (0{,}1)$: field of study.
  - Assumption: $\frac{dC}{da} < 0$
  - α_{jt}: productivity in each task, is unobserved.
- Define individual's productivity in task i

$$\alpha_{jt}(i) = f(a, s, F_j, \Delta_j)$$

  - F_j: career specific learning that happens in school.
  - $\Delta_j \in [0,1]$: career specific rate of task change.

MODEL SETUP - LABOR PRODUCTIVITY

- We refer to the year that a task was introduced as the task's vintage v
- let the worker's productivity in each task, industry, and year be,

$$\alpha_{ijt}(a, s, F_j) = \begin{cases} (F_j S^*) + \left[a(t+1)\right] = \alpha_{jt}^{PRE}; & \text{if } v = 0 \\ \\ a(t-v+1) = \alpha_{jt}^{POST(v)}; & \text{if } v > 0 \end{cases}$$

- Assumption: a fraction Δ_j of tasks are replaced by new tasks.
- Define g_{it} as the weight of tasks coming from each vintage at time t.

$$\begin{cases} g_{it}(0) = (1-\Delta_j)^t; & v = 0 \\ g_{it}(v) = \Delta_j (1-\Delta_j)^{t-v}; & v > 0 \end{cases}$$

MODEL SETUP - EQUILIBRIUM WAGE

- By zero profit condition in perfect competitive market, in equilibrium, task price equals to productivity: $p_{ijt} = \alpha_{ijt}(a, s)$
- we obtain the equilibrium wages by integrating over the prices for tasks performed in career j and time t, with the weight g_{it}:

$$W_{jt} = \int_0^1 p_{ijt} di = \int_0^1 \alpha_{ijt}(a, s) di$$

$$= \left\{(1 - \Delta_j)^t \alpha_{jt}^{PRE}\right\} + \left\{\sum_{v=1}^{t:t>0} \Delta_j (1 - \Delta_j)^{t-v} \alpha_{jt}^{POST(v)}\right\}$$

  - When t = 0 (i.e. the year of graduation),

$$W_{j,t=0} = (F_j S^*) + a$$

  - When t = 1,

$$W_{j,t=1} = (1 - \Delta_j)(F_j S^* + 2a) + \Delta_j a$$

- Wage is increasing with increased productivity in older tasks and decreasing with the entry of new tasks.

PREDICTION 1 AND 2

The model yields 4 key predictions.

1. Wage growth is lower in careers with higher rates of task change.
   - Test the prediction by running the regression:

$$\ln(\mathrm{earn})_{it} = \alpha_{it} + \sum_{a}^{A} \beta_a a_{it} + \sum_{a}^{A} \gamma_a (a_{it} * \mathrm{TaskChange}_{it}^{0}) + \delta X_{it} + \theta_t + \epsilon_{it}$$

   - The results shows jobs with higher rates of task change have flatter age - earnings profile, which confirms the prediction.

2. Workers are more likely to sort out of high Δ_j careers over time.
   -

$$\mathrm{TaskChange}_{it}^{0} = \alpha_{it} + \sum_{a=23,24}^{a=49,50} \beta_a a_{it} + \delta X_{it} + \theta_t + \epsilon_{it}$$

   - Results: workers in jobs with a one standard deviation higher value of TaskChange are about 1 percent point more likely to be ages 25-26 than ages 39-40.

PREDICTION 3

3. Technical Careers have higher starting wages, and high ability workers are more likely to begin in technical careers.

    - Intuition: high ability workers have a lower cost of learning technical subjects.

4. High ability workers will sort out of STEM careers over time.

    - Intuition: the returns to being a fast learner are greater in jobs with lower rates of task change.
    - Test regression:

$$y_{it} = \alpha_{it} + AGE_{it} + \beta STEM_i + \gamma AFQT_i + \theta AGE_i * AFQT_i + \delta X_{it} + \epsilon it$$

    - Find a negative and a statistically significant coefficient on the interaction term of AGE and ability.

CONCLUSION AND CONTRIBUTION

- Presents new evidence on the life-cycle returns to STEM majors and STEM careers.
- The flatter wage growth pattern in STEM is due to the changing nature of STEM jobs themselves.
- The paper formalizes the key mechanism of job task change with a simple model of education of career choice.
- The results inform policy trade offs between investment in specific and general education.

Thank you.