Skill-Biased Innovation Activities: Evidence from Hungarian Firms

Attila Lindner [1] **Balázs Muraközy** [2] Balázs Reizer[2]

[1]UCL and CERS

[2]CERS Hungarian Academy of Sciences

5 January 2019, ASSA

Table of Contents

Motivation

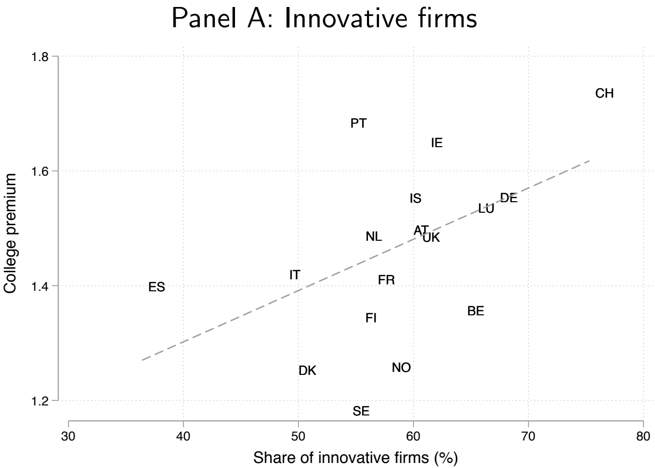
- Innovation is a key driver of economic growth
- But innovation also leads to reallocation of resources
- Relationship between innovation and inequality is a central policy question
- Empirical evidence often relies on indirect measures or focuses on the role of high novelty (e.g. high value patents, R&D)
- Economy-wide technological change consists of high novelty innovations followed by many low novelty innovations as part of the diffusion process (Bresnahan and Trajtenberg, 1995)

Broadly defined innovation

- Most innovation activity has a relatively **low novelty content**. In European countries
  - 25-35 percent of process innovator firms introduced a process that was "new to the market"
  - 5-25 percent of product innovator enterprises introduced products which were "new to the world"
  - 30-50% of product/process innovators relied on R&D
- This paper focuses on **broadly defined innovation** as measured by Innovation Surveys
  - Introduce product, process, organizational solution, which is **new to firm** but not necessarily new to the world/market

Broadly Defined Innovation and the College Premium

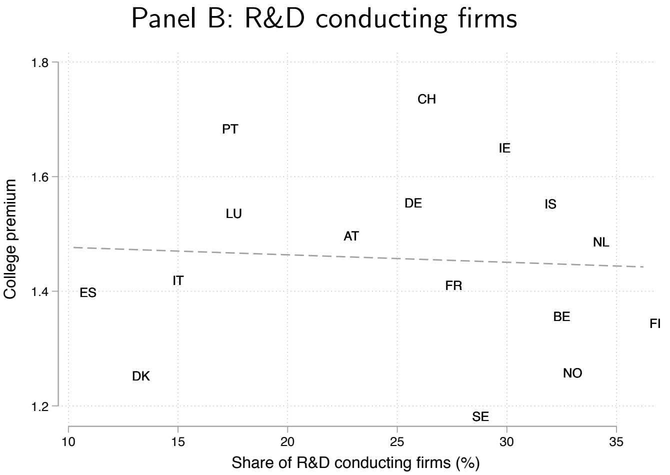
Cross-country evidence



Note: Community Innovation Survey and Structure of Earning Survey, 2014, source: Eurostat.

R&D and the College Premium

Cross-country evidence



Note: Community Innovation Survey and Structure of Earning Survey, 2014, source: Eurostat.

This Paper

- Is broadly defined innovation skill biased?
- Are different forms of innovation more or less skill biased?
  - Low vs. high novelty
  - Technological vs. organizational
  - Product vs. process vs. organizational

Empirical Strategy

- Motivated by Abowd et al. (1999), Card et al. (2013) and Song et al. (2015) we focus on the **role of firms**
- Diff-in-diff-type identification strategy:
  - Take two initially non-innovative and similar firms; one of them starts to innovate
  - Compare the subsequent change in their skill demand, measured by the **college ratio** and the **college premium**
- Additional evidence in the paper based country-industry-level relationship between innovation activities and subsequent change in skill demand

Table of Contents

Conceptual Framework

Setup

- In competitive labor market, the skill premium should not change in such a comparison
- Therefore, such an empirical exercise should be guided by a model of imperfectly competitive labor markets
- Follow Card, Cardoso, Heining and Kline (2018)
- Focus on how Hicks-neutral and skill-biased technological change affects the skill ratio and the skill premium to distinguish between the two

Conceptual Framework

Setup

- Two types of labor, skilled (H) and unskilled (L)
- Iso-elastic type-specific supply curves for firm j

$$\ln L_j(w_{Lj}) = \ln(L\lambda_L) + \beta_L \ln w_{Lj} + a_{Lj}$$

$$\ln H_j(w_{Hj}) = \ln(H\lambda_H) + \beta_H \ln w_{Hj} + a_{Hj}$$

  - w_{Lj} and w_{Hj} are firm-skill specific wages
  - β_L and β_H are skill-specific elasticities
  - λ_H and λ_L are type-specific constants
  - a_{Lj} and a_{Hj} are firm-skill-specific amenities

Conceptual Framework

Setup: CES

- Assume that the production function is CES

$$Y_j = TFPR_j \left[(1-\theta_j) L_j^{\frac{\sigma-1}{\sigma}} + \theta_j H_j^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

  - Y_j is value added
  - $TFPR_j$ is (revenue) productivity (**Hicks-neutral term**)
  - θ_j is the relative productivity of skilled labor (**Skill-biased term**)

Conceptual Framework

Results: Perfect substitutes

- Start with a special case when $\sigma = \infty$
- Under these conditions the skill premium in firm j is

$$\ln \frac{w_{Hj}}{w_{Lj}} = \ln \frac{\beta_H}{1+\beta_H} - \ln \frac{\beta_L}{1+\beta_L} + \ln \frac{\theta_j}{1-\theta_j}$$

- The skill ratio is

$$\ln \frac{H_j}{L_j} = C + \frac{a_{Hj}}{a_{Lj}} + \beta_H \ln \theta_j - \beta_L \ln \frac{1}{1-\theta_j} + (\beta_H - \beta_L) \ln TFPR_j$$

- Hicks-neutral change does not affect the skill premium, but leads to an increase in the skill ratio if $\beta_H > \beta_L$
- Skill augmenting increase in θ_j increases the skill premium and also the skill ratio

Conceptual Framework

- For arbitrary σ, the skill-premium is

$$\ln \frac{w_{Hj}}{w_{Lj}} = \ln \frac{\beta_H}{1+\beta_H} - \ln \frac{\beta_L}{1+\beta_L} + \ln \frac{\theta_j}{1-\theta_j} - \frac{1}{\sigma} \ln \frac{H_j}{L_j} \tag{1}$$

- Wage-premium change conditional of the skill ratio suggest that innovation is skill-biased
- No closed form solution for the skill ratio, which is a function of both the Hicks-neutral and the skill-biased term

Related literature

- Aggregate evidence on skill biased technological change and wage inequality (Acemoglu 2002; Goldin and Katz 2010)
- The role of firms in income inequality (Abowd et al. 1999; Card et al. 2013; Song et al. 2015)
- R&D, patents and wage inequality (Boler 2015; Aghion et al 2017, Kline et al., 2018)
- Skill biased IT (Autor, Levy, Murnane, 2003; Bresnahan et al. 2002; Akerman et al. 2015) and related organizational change (Caroli and Van Reenen, 2001).
- Innovation activities and firm's performance (Crepon et al. 1998, Griffith et al. 2006)

Table of Contents

Data and methods

Community Innovation Survey (CIS)

- A **large biannual Community Innovation Survey** asking for detailed information on firms' innovative activities
  - 6 waves 2004-2014
  - app. 5,000 firms per wave
  - Conducted in all EU countries
  - Questions refers to activities in the preceding 3 years
- **Structure of Earnings Survey**
  - Detailed information on demographics, wages, hours for workers at a random sample of firms
- **Corporate Income Tax data**
  - Balance sheet information and income statement for each year

Effect on Skill Premia

Individual-level regressions

- Estimate:

$$\ln wage_{ijt} = \beta_u * innovation_{jt} + \beta_s * innovation_{jt} \times college_{it} + \\ + \delta * skillratio_{jt} + \gamma * X_{ijt} + \varphi_j + \varsigma_{s(i)t} + \varepsilon_{ijt}$$

  - where i indexes employees, j firms, t years
  - $innovation_{jt}$ is the dummy showing whether the firm innovated in the corresponding CIS wave or in any of the previous two waves
  - X_{ijt} are the usual Mincer-type controls,
  - φ_j are firm fixed effects, while $\varsigma_{s(i)t}$ are skill-year fixed effects
  - including $skillratio_{jt}$ is motivated by the conceptual framework
- β_u shows the wage extra wage premium of non-college workers in innovative firms, while β_s shows the extra college premium

Effect on Skill Premia

Econometric problems

- Innovation might change the **composition of the workforce**
  - Follow Csillag and Koren (2017) with proxying this nonparemetrically with skill-occupation-age cells ($\hat{p}$)
  - Robust when restricting to incumbents
  - We can include personal effects for a subset of individuals

Effect on Skill Premia

Econometric problems

- Innovating firms might pay higher wage or wage premium premium even prior to innovation
  - Include **firm fixed effects**
  - **Matching** with the aim is to ensure **common support**
    - Restrict our sample to firms which were sampled at least twice in the CIS, and were **not innovative in the first period**
    - Consider the firms which started to innovate sometime later as **treated**
    - Do a **propensity score matching** based on characteristics in the first year a firm appears in the CIS
  - Alternatively, focus on **switcher sample**

Table of Contents

Main results

LHS: log wage	(1)	(2)	(3)	(4)
Innovation	0.201***	0.166***	-0.005	0.004
	(0.022)	(0.019)	(0.009)	(0.009)
Innovation x College	0.085***	0.100***	0.083***	0.055***
	(0.027)	(0.023)	(0.020)	(0.020)
Skill-year FE	yes	yes	yes	yes
Mincer variables		yes	yes	yes
$\hat{p}$			yes	yes
Firm FE			yes	yes
Matched sample			yes	
Switcher sample				yes
Observations	785,443	785,443	157,714	105,143
R-squared	0.438	0.692	0.699	0.699
Firms	6236	6236	1075	870

Note: This table shows the results of individual-level regressions, with ln wage as the dependent variable. All columns include skill-year fixed effects. Standard errors are clustered at the firm level.

Additional Results

- Skill-premium is **persistent**
  - Driven by a permanent increase in base salary rather than temporarily higher bonuses
  - Suggests that it is not driven by higher efforts by college educated workers
- College premium is **not driven by the task content**
  - Innovation is associated with an increased premium of non-routine workers
  - But this does not affect the estimates for the college premium

Table of Contents

Heterogeneity: Novelty

LHS: log wage	(1)	(2)	(3)	(4)	(5)
Innov x college	0.083***	0.080***	0.090***	0.082***	0.082***
	(0.020)	(0.021)	(0.020)	(0.020)	(0.022)
Innov x R&D x college		0.005			0.015
		(0.026)			(0.025)
Innov x new x college			-0.028		-0.037
			(0.031)		(0.033)
Innov x developed x college				0.004	0.007
				(0.024)	(0.021)
Innovation, novelty	yes	yes	yes	yes	yes
Skill-year FE	yes	yes	yes	yes	yes
Mincer variables	yes	yes	yes	yes	yes
$\hat{p}$	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes
Matched sample	yes	yes	yes	yes	yes
Observations	157,714	157,714	157,714	157,714	157,714
R-squared	0.699	0.699	0.699	0.699	0.699

Heterogeneity: Type of innovation

LHS: log wage	(1)	(2)
Org x College	0.022	0.024
	(0.021)	(0.021)
Tech. x college	0.078***	
	(0.020)	
Process x college		0.053**
		(0.025)
Product x college		0.030
		(0.027)
Innovation type, novelty	yes	yes
Skill-year FE	yes	yes
Mincer variables	yes	yes
$\hat{p}$	yes	yes
Firm FE	yes	yes
Matched sample	yes	yes
Observations	157,714	157,714
R-squared	0.699	0.699

Table of Contents

Decomposition exercise

- The role of low-novelty innovation in **aggregate cross-sectional** college premium
  1. **Counterfactual scenario 1**: All high-novelty innovators become low-novelty
     - We switch the **R&D dummy to zero** for all firms, and predict the wages for each worker
     - Calculate the college premium from these predicted wages
  2. **Counterfactual scenario 2**: No firms innovate
     - We switch the **innovation dummy to zero** for all firms, and predict the wages for each workers.
     - Calculate the college premium from these predicted wages

The role of innovation in the cross sectional college premium

Panel A: Matched sample

ln (wage):	(1) Observed	(2) No high innov.	(3) No innov
Low skilled wage	12.130	12.129	12.138
College wage	12.930	12.926	12.880
College wage premium	0.800	0.797	0.742

Panel B: Full sample

ln (wage):	(1) Observed	(2) No high innov.	(3) No innov
Low skilled wage	12.134	12.137	12.150
College wage	12.947	12.933	12.884
College wage premium	0.813	0.796	0.734

Conclusions

- Innovation activities are skill biased:
  - They increase share of college educated
  - They increase wage premium
- Novelty value does not matter much
  - High novelty and low novelty innovation is similarly skill biased
  - Given its prevalence in economy low novelty innovation is a key driver of inequality
- Both technological and organizational innovation are skill biased
  - Technological innovation increase skill premium
  - Organizational innovation increase skill ratio