Skill-Biased Innovation Activities: Evidence from Hungarian Firms

Attila Lindner [1] **Balázs Muraközy**[2] Balázs Reizer[3]

[1]UCL and MTA-KRTK

[2]MTA-KRTK

[3]MTA-KRTK

28 November 2018, University College London

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)

Motivation

IBMs introduction of the PC in the USA, 1980s

Time	Event	Type	Novelty	Mechanism	People Affected
to 1981	IMB R&D	R&D	High	Skill-intensive	12

Motivation

IBMs introduction of the PC in the USA, 1980s

Time	Event	Type	Novelty	Mechanism	People Affected
to 1981	IMB R&D	R&D	High	Skill-intensive	12
1981	Intro of IBM PC	Product	High	Nelson-Phelps	165,000

Motivation

IBMs introduction of the PC in the USA, 1980s

Time	Event	Type	Novelty	Mechanism	People Affected
to 1981	IMB R&D	R&D	High	Skill-intensive	12
1981	Intro of IBM PC	Product	High	Nelson-Phelps	165,000
1980s	Others produce PC	Product	Low	Nelson-Phelps	500,000

Motivation

IBMs introduction of the PC in the USA, 1980s

Time	Event	Type	Novelty	Mechanism	People Affected
to 1981	IMB R&D	R&D	High	Skill-intensive	12
1981	Intro of IBM PC	Product	High	Nelson-Phelps	165,000
1980s	Others produce PC	Product	Low	Nelson-Phelps	500,000
1980s	Firms adopt PC	Process	Low	Capital-skill comp	30 m

Motivation

IBMs introduction of the PC in the USA, 1980s

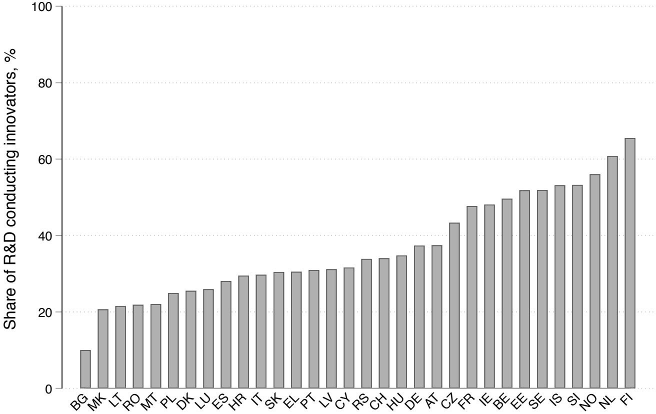
Time	Event	Type	Novelty	Mechanism	People Affected
to 1981	IMB R&D	R&D	High	Skill-intensive	12
1981	Intro of IBM PC	Product	High	Nelson-Phelps	165,000
1980s	Others produce PC	Product	Low	Nelson-Phelps	500,000
1980s	Firms adopt PC	Process	Low	Capital-skill comp	30 m
1980s	Reorganization	Organization	Low	Milgrom-Roberts	???

Motivation

How to think about low novelty innovation

- High novelty innovation
  - Develop technology which is new to the World/Market
  - Often proxied by R&D, patents
- Low novelty innovation
  - Introduce product, process, organizational solution, which is not new to the World/market
  - If the technology exists, it is likely to be adoption of technology
  - This is also an important part of innovation activities in the Schumpeterian sense (Fagerberg, 2007)

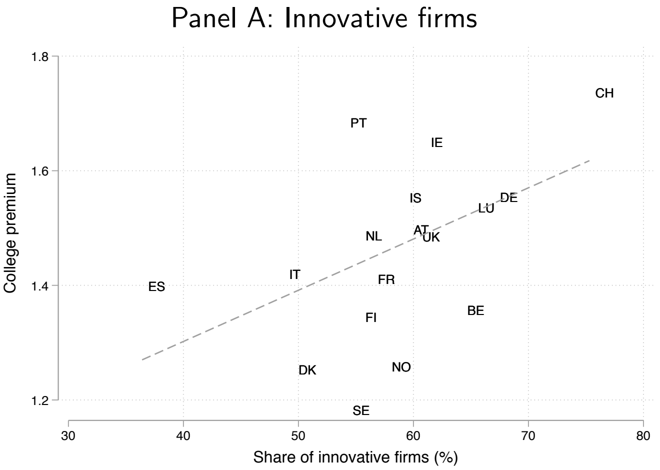
Share of R&D conducting firms in all innovators



Note: Community Innovation Survey 2014, source: Eurostat.

Broadly Defined Innovation and the College Premium

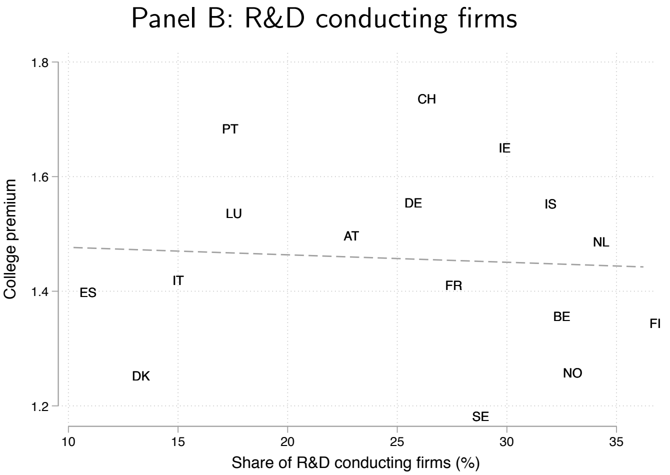
Cross-country evidence



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?

Empirical Strategy

Diff-in-Diff style Strategy

- **Worker-level** regressions on **college premium** identifying from firm-level change in innovation activities in Hungary
  - Exploit unique linked data
    - Community Innovation Survey
    - Employee data
    - Administrative balance sheet data
  - To minimize endogeneity concerns we use firm FEs, matching, and switcher sample
- **Firm-level** relationship between innovation activities and subsequent long change in **college share**
- **Country-industry-level** relationship between innovation activities and subsequent long change in **college share** and **college premium** in 25 European Countries

Preview of the Results

- 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 share

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)

Overview

Table of Contents

Conceptual Framework

Setup

- Follow Card, Cardoso, Heining and Kline (2018)
- Assume imperfect competition in the labor market
- 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: Perfect substitutes

- Assume that the production function is linear

$$Y_j = TFPR_j[(1-\theta_j)L_j + \theta_j H_j]$$

  - Y_j is value added
  - $TFPR_j$ is (revenue) productivity
  - θ_j is the relative productivity of skilled labor

Conceptual Framework

Results: Perfect substitutes

- Under these conditions the wage 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 skilled share 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 in TFPR does not affect the skill premium, but leads to an increase in skill share if $\beta_H > \beta_L$
- Skill augmenting increase in θ_j increases the skill premium and also the skill share

Conceptual Framework

Setup: CES

- Assume now that the production function is CES

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

- The relative wages are:

$$\ln \frac{w_{Hj}}{w_{Lj}} = \ln \frac{\beta_H}{1+\beta_H} - \ln \frac{\beta_L}{1+\beta_L} + \ln \frac{\theta_j}{1-\theta_j} + (\rho - 1) \ln \frac{H_j}{L_j}$$

- From which

$$\frac{\partial \ln \frac{w_{Hj}}{w_{Lj}}}{\partial TFPR_j} = (\rho - 1) \frac{\partial \ln \frac{H_j}{L_j}}{\partial TFPR_j}$$

$$\frac{\partial \ln \frac{w_{Hj}}{w_{Lj}}}{\partial \theta_j} = \frac{1}{\theta_j} + 1 - \theta_j + (\rho - 1) \frac{\partial \ln \frac{H_j}{L_j}}{\partial \theta_j}$$

Conceptual Framework

Theories

- Innovation can shift θ_j through the following channels (Violante, 2008)
  - Educated people deal better with technological change (Nelson and Phelps, 1966)
    - Mostly related to technological/process innovation
  - Capital complements skills (Grilliches, 1969; Krussel, Ohanian, Ríos-Rull and Violante, 2000)
    - Mostly related to technological/process innovation
  - Information technology tend to lead to flatter organizations (Milgrom and Roberts, 1986)
    - Captured by organizational innovation

Table of Contents

Data

Community Innovation Survey (CIS)

- A **large biannual 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**

Data

Community Innovation Survey (CIS)

- **Broad range** of innovation activities
  - *product* innovation (market introduction of a new or significantly improved good or service)
  - *process* (implementation of a new or significantly improved production process, distribution method, or supporting activity)
  - *organizational* (new organizational method in business practices, workplace organization or external relations)
- **Broad definition** of innovation in terms of **novelty**
  - Must be new to your enterprise, but they do not need to be new to your market. [...] could have been originally developed by your enterprise or by other enterprises or institutions.
- Novelty is measured in detail
  - R&D, new to the market, who developed it

Data

Employee and firm information

- **Structure of Earnings Survey**
  - all firms with more than 20 employees, a random sample of firms with 5-20 employees
  - detailed information on demographics, wages, hours for workers at the firm in May 31.
- **Corporate Income Tax data**
  - universe of double book keeping firms
  - balance sheet information and income statement for each year

Observations Firm-level descriptives

Table of Contents

Effect on Skill Premia

Individual-level regressions

- We estimate individual-level regressions to estimate the effect on the college premium

$$\ln wage_{ijt} = \beta_u * innovation_{jt} + \beta_s * innovation_{jt} \times college_{it} + \gamma * X_{ijt} + \varphi_j + \varsigma_{st} + \varepsilon_{ijt}$$

  - where i indexes employees, j firms, t years and s skill levels.
  - $innovation_{jt}$ 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 ς_{st} are skill-year fixed effects
- 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

- Unobserved **worker** heterogeneity
  - We do not observe worker identifiers
    - Follow Csillag and Koren (2017) with proxying this nonparametrically with skill-occupation-age cells ($\hat{p}$)
    - Robust when restricting to incumbents
- Unobserved **firm** heterogeneity: wage **levels**
  - Future innovative firms may already pay higher wages
    - Include firm fixed effects
- Unobserved **firm** heterogeneity: skill **premium**
  - Future innovative firms may already allocate more complex task and responsibility to high skilled workers and pay higher premia
    - Matching, Switchers

Effect on Skill Premia

Matching and switchers

- **Matching** with the aim is to ensure **common support**
  1. Restrict our sample to firms which were sampled at least twice in the CIS, and were **not innovative in the first period**
  2. Consider the firms which started to innovate sometime later as **treated**
  3. Do a **propensity score matching** based on characteristics in the first year a firm appears in the CIS
     - Use 1-digit industry dummies, year dummies, log employment, log productivity, log wage premium, ownership.
     - Use from the CIS: the main market of the firm, the types of funding it received and its main information sources (Griffith et al., 2006).
- Alternatively focus on **switcher sample**

Main worker-level results

LHS: log wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Innovation	0.201***	0.166***	0.165***	-0.026**	-0.024**	-0.005	-0.007
	(0.022)	(0.019)	(0.018)	(0.013)	(0.010)	(0.009)	(0.010)
Innovation x College	0.085***	0.100***	0.085***	0.114***	0.119***	0.083***	0.085***
	(0.027)	(0.023)	(0.022)	(0.013)	(0.013)	(0.020)	(0.021)
Innovation pre-trend					-0.001		-0.007
					(0.020)		(0.014)
Innovation pre-trend x College					0.075***		0.013
					(0.022)		(0.023)
Skill-year FE	yes	yes	yes	yes	yes	yes	yes
Mincer variables		yes	yes	yes	yes	yes	yes
$\hat{p}$			yes	yes	yes	yes	yes
Firm FE				yes	yes	yes	yes
Matched sample						yes	yes
Observations	785,443	785,443	785,443	785,419	785,419	157,714	157,714
R-squared	0.438	0.507	0.517	0.717	0.717	0.699	0.699
Firms	6236	6236	6236	6212	6212	1075	1075
F-value for pre-trend					3.458		12.13
p-value for ptre-trend					0.0630		0.000516

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.

Robustness checks

- Switcher sample Table
  - Restrict the sample to firm switching from non-innovation to innovation
  - Identify only from time variation
- Matching
  - Kernel matching
  - No weights, just common support
- Heterogeneity in premia
  - Industry-skill year FE, Occupation-year FE, Restrict to domestically-owned
- Timing assumption
  - Innovation defined only based on the current wave or the 2 previous ones

Table of Contents

Firm-level regression

Methodology

- We follow Caroli and Van Reenen (2001) and estimate estimate long-difference regressions

$$\Delta y_{jt} = \beta * innovation_{jt} + \gamma * \Delta X_{jt} + \delta * y_{jt-1} + \eta_{kt} + \epsilon_{jt}$$

- j indexes firms, t years
- Δy_{jt} is the change between year t and $t + 6$.
- $innovation_{jt}$ is a dummy, showing whether the firm was innovative in the corresponding or the previous CIS wave.
- ΔX_{jt} is the long difference in value added and capital, which we include only for the college share equations.

Firm-level regression

Identification issues

- Firm heterogeneity
  - Differentiating the dependent variable
  - Results are robust to controling/not controling for lagged level of the dependent variable
- Simultaneity and timing
  - Effect of lagged innovation on future long term change
- Industry-level shocks
  - Industry-year fixed effects

Firm-level regression

LHS:	(1) college wage share	(2) college employment share	(3) wage rate	(4) TFP (ACF)	(5) TFP (LP)	(6) ln employment
Innovation	0.017***	0.019**	0.030	0.061**	0.050**	0.030
	(0.004)	(0.008)	(0.023)	(0.025)	(0.022)	(0.020)
ln capital (d)	-0.006	-0.007	-0.011			
	(0.004)	(0.007)	(0.019)			
ln value added (d)	-0.005	-0.007	0.010			
	(0.005)	(0.008)	(0.022)			
Dependent variable (t-1)	yes	yes	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes	yes	yes
Observations	2,153	2,153	1,386	2,122	2,122	2,122
R-squared	0.099	0.095	0.207	0.140	0.148	0.144

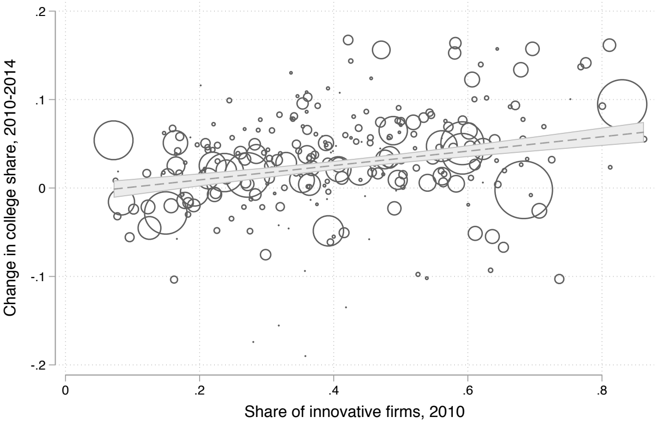
Note: This table shows firm-level regressions with long (6-year) differences of the wage and employment shares and TFP on the left hand side. Standard errors are clustered at the firm level.

Country-industry-level regressions

- Similar long-difference specifications, following Machin-van Reenen (1998)
- 25 European countries, 1-digit industries
- CIS from 2010
- Structure of Earnings Surveys from 2010 and 2014
- Weight with the number of firms in the CIS

Country-industry-level regressions

Premium of college workers



Table

Country-industry-level regressions

Premium of college workers

Table

Table of Contents

Novelty

- Are innovations with a **high novelty value more skill-biased** than those with a low novelty value?
- Novelty is measured by three dummies:
  - Did it conduct **R&D**?
  - Was the product of process **new to the market/country**?
  - Was the innovation **developed by the firm** itself or by others?
- We include triple interactions of *innovation* $\times$ *college* $\times$ *high* to the individual regressions
  - It captures the **extra** college premium of **high-novelty** innovation relative to low novelty

Novelty: Individual level

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

Firm-level

Type

- What **type** of innovation drives inequality among low novelty innovation?
  - Technological
    - Product/Service
    - Process
  - Organizational
- We include **separate dummies** for each type of innovation into the worker level regression, each interacted with college
  - A firm can conduct multiple types of innovation
  - Also control for novelty value, proxied by the R&D dummy

Technological and organizational innovation: Individual level

LHS: log wage	(1)	(2)	(3)	(4)
Tech. x college	0.078***		0.087***	
	(0.020)		(0.023)	
Org x College	0.022	0.024	0.024	0.025
	(0.021)	(0.021)	(0.020)	(0.021)
Process x college		0.053**		0.058**
		(0.025)		(0.023)
Product x college		0.030		0.036
		(0.027)		(0.031)
Innov x R&D x college			-0.020	-0.018
			(0.028)	(0.030)
Innovation type, novelty	yes	yes	yes	yes
Skill-year FE	yes	yes	yes	yes
Mincer variables	yes	yes	yes	yes
$\hat{p}$	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Matched sample	yes	yes	yes	yes
Observations	157,714	157,714	157,714	157,714
R-squared	0.699	0.699	0.699	0.699

Firm-level

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 demand

References

Number of observations

	(1)	(2)	(3)
Year	CIS	CIS balance sheet	CIS balance sheet structure of earnings
2003	3,950	3,190	1,483
2004	3,950	3,268	1,408
2005	5,094	4,063	2,275
2006	5,094	4,149	1,995
2007	5,390	4,365	1,796
2008	5,390	4,466	2,216
2009	5,120	4,134	1,811
2010	5,120	4,211	1,740
2011	5,482	4,458	1,981
2012	5,482	4,430	2,126
2013	7,243	5,849	2,407
2014	7,243	5,912	2,512
Total	64,558	52,495	23,750

Back to Main

Descriptives at the firm level

Variable	Non-innovative	Innovative	diff	t-value
Average age of empl.	42.1	41.3	-0.8	-6.94
	(0.09)	(0.10)		
Share of female empl.	0.21	0.19	-0.02	-3.43
	(0.01)	(0.00)		
Average year of education	11.4	11.8	0.3	11.09
	(0.02)	(0.03)		
Share of college grad.	0.12	0.18	0.05	12.73
	(0.00)	(0.00)		
Average wage	173,087	206,746	33,659	12.90
	(1,672.11)	(2,446.14)		
Foreign-owned (dummy)	0.31	0.41	0.11	8.71
	(0.01)	(0.01)		
Number of employees	159	435	276	6.91
	(7.43)	(44.85)		
ln(tangible capital/employees)	7.95	8.46	0.51	15.08
	(0.03)	(0.03)		
ln(value added/employees)	8.24	8.54	0.30	14.72
	(0.01)	(0.02)		

Back to Main

Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LHS: log wage	Industry-skill-year-FE	Occupation-year-FE	Same wave	Kernel matching	Switcher sample	CDM instruments	Only domestic
Innovation	-0.001	-0.005	-0.009	-0.008	0.004	-0.029	0.003
	(0.009)	(0.009)	(0.007)	(0.009)	(0.009)	(0.028)	(0.011)
Innovation x College	0.067***	0.080***	0.070***	0.092***	0.055***	0.081***	0.083***
	(0.018)	(0.019)	(0.019)	(0.020)	(0.020)	(0.031)	(0.030)
Sample	matched (NN)	matched (NN)	matched (NN)	matched (kernel)	switcher	matched (NN)	matched (NN) domestic
Skill-year FE	yes	yes	yes	yes	yes	yes	yes
Mincer variables	yes	yes	yes	yes	yes	yes	yes
$\hat{p}$	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes
Industry-skill-year FE	yes	no	no	no	no	no	no
Occupation-year FE	no	yes	no	no	no	no	no
# waves for innov. var	3	3	1	3	3	1	3
Observations	157,709	157,714	142,249	226,422	105,143	142,249	88,661
R-squared	0.704	0.754	0.697	0.701	0.692	0.697	0.685

Back to Main

Country-industry-level regressions

Share of college workers

	College share change, 2010-2014			
	(1)	(2)	(3)	(4)
Share of innovative firms (2010)	0.104**	0.166***	0.129**	0.112**
	(0.050)	(0.050)	(0.053)	(0.053)
Share of R&D conducting firms (2010)	-0.009	-0.099**	-0.031	
	(0.050)	(0.039)	(0.059)	
R&D intensity (2010)				-0.002
				(0.002)
College share (2010)	-0.045	0.014	-0.243***	-0.245***
	(0.038)	(0.019)	(0.078)	(0.076)
Country FE		yes	yes	yes
Industry FE			yes	yes
Observations	155	155	155	155
R-squared	0.139	0.713	0.817	0.818

Back to Main

Country-industry-level regressions

Premium of college workers

	College premium change, 2010-2014			
	(1)	(2)	(3)	(4)
Share of innovative firms (2010)	0.412**	0.306**	0.167	0.180
	(0.153)	(0.125)	(0.126)	(0.137)
Share of R&D conducting firms (2010)	-0.228**	-0.066	-0.003	
	(0.098)	(0.051)	(0.117)	
R&D intensity (2010)				-0.005
				(0.005)
College premium (2010)	0.098**	-0.060	-0.187**	-0.181**
	(0.047)	(0.079)	(0.085)	(0.084)
Country FE		yes	yes	yes
Industry FE			yes	yes
Observations	151	151	151	151
R-squared	0.211	0.674	0.731	0.732

Main

Novelty: firm-level

LHS:	College emp. share	College wage share	TFP (ACF)	TFP (LP)
	(1)	(2)	(3)	(4)
Innovation	0.011**	0.007	0.035	0.030
	(0.005)	(0.009)	(0.028)	(0.026)
Innovation x R&D	0.013**	0.026***	0.055*	0.045
	(0.006)	(0.010)	(0.033)	(0.029)
Value added (d)	yes	yes		
Capital (d)	yes	yes		
Dependent var. (t-1)	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes
Dependent var. (t-1)	yes	yes	yes	yes
Observations	2,153	2,153	2,122	2,122
R-squared	0.102	0.100	0.141	0.149

Main

Technological and organizational innovation: firm-level

LHS:	College emp. share (1)	College wage share (2)	TFP (ACF) (3)	TFP (LP) (4)
Innovation x R&D	0.010	0.025**	0.067*	0.058*
	(0.006)	(0.010)	(0.035)	(0.031)
Technological inn.	0.007	0.004	-0.008	-0.018
	(0.005)	(0.009)	(0.032)	(0.030)
Organizational inn.	0.009*	0.005	0.026	0.032
	(0.005)	(0.008)	(0.029)	(0.025)
Value added (d)	yes	yes		
Capital (d)	yes	yes		
Dependent var. (t-1)	yes	yes	yes	yes
Industry-year FE	yes	yes	yes	yes
Dependent var. (t-1)	yes	yes	yes	yes
Observations	2,153	2,153	2,122	2,122
R-squared	0.103	0.100	0.141	0.149

Main