Recruitment, knowledge integration and modes of innovation

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Does recruiting affect innovation?

Summary.

Summary.

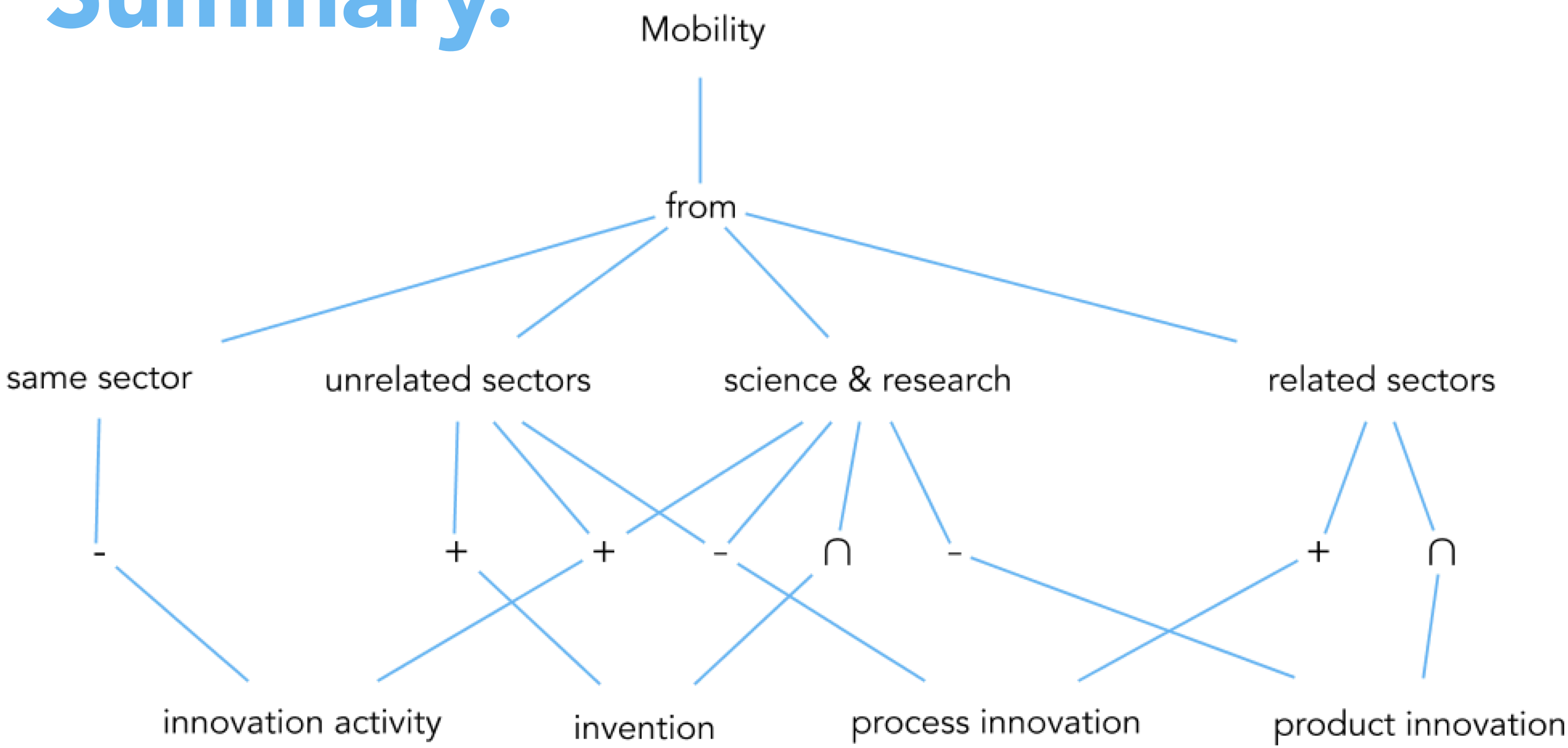
- Mobility of human resources generates / fosters
  - diffusion of competences / knowledge
  - work practices / routine / work ethics
  - interpersonal networks
- These networks link organizations from different technological and institutional domains

- We investigate how recruiting (past inflow of human resources) into firms affect the receiving firms innovation performance.

- Use large scale Norwegian data on firm level innovation and labor mobility

- We find: labor mobility from different sources affect innovation differently.

Summary.


Mobility
from
same sector
unrelated sectors
science & research
related sectors
-
+
+
-
∩
-
+
∩
innovation activity
invention
process innovation
product innovation

Structure.

- Framework
- Recruiting
- Data, Methods & Results
- Outlook

Framework:

Knowledge Generation & Knowledge Transfer.

Innovation System.

- As a network of heterogeneous actors (Innovation system)
  - Firms / education org / research org / government
- Various types of links and interaction
- Jointly generating, accumulating and diffusing
- Knowledge, competences and artifacts

- Target: Facilitate the development, diffusion and utilization of new technologies and innovations (e.g. Edquist, 2005)

Micro-Foundation of IS.

- Firms recognize that
  - Competitiveness depends on a firm's access to resources and capabilities; resource based view (e.g. Wernerfelt, 1984)
    - Resources and capabilities are heterogeneous across firms (Peteraf, 1993)
  - In particular knowledge is a core determinant of competitiveness; knowledge based view (e.g. Grant, 1996)
    - Firm's competitiveness hinges on its ability to combine and recombine old and new knowledge through routines (e.g. Nelson & Winter, 1982)
  - Yet, one single actor cannot keep abreast of all relevant knowledge domains that represent an opportunity

Micro-Foundation of IS.

- Competitiveness depends on the firms ability to compose, establish and maintain (Nicholls-Nixon & Woo, 2003)
  - Internal processes for knowledge generation
  - External interfaces for knowledge transfer
- These external interfaces are the foundations of interactive learning and knowledge development in a wider innovation system (Guiliani & Bell, 2005; Graf, 2010)

Knowl. Generation & Transfer.

- Internal knowledge generation
  - Internal innovation activities and R&D
  - Experience based DUI (doing using interacting)

- External interfacing for knowledge transfer
  - Recruiting
  - Search
  - Collaboration
  - Sourcing

External Interfaces:
Recruiting.

Recruiting.

- New employees enter with
  - Ideas
  - Information
  - Interpersonal network linkages (Agrawal, et al., 2006)
  - Work routines

- These reflect the
  - Organizational, technological and institutional domains covered by their prior carrier paths

- Recruitment might extend the search space of firms (Katila 2002)

- Under certain conditions this may increase the diversity of the firm's knowledge bases and hence support innovation

Recruiting.

- Recruiting (HR) is a generic support process supplying the general workforce to the firm
  - Labor mobility *per se* into the firm probably no effect
  - Different categories of mobility must be distinguished (Boschma et al., 2009)

- Differentiation of mobility types based on cognitive distance and relative absorptive capacity
  - Absorptive capacity contingent on characteristics of source and recipient
  - Cognitive distance = Similarity of knowledge base and experience

Recruiting.

- We differentiate labor mobility by the sector of the previous employment
- Build on concept of relatedness of sectors

  Frenken et al. (2007); Boschma et al. (2009)

  - Mobility from the same sector
  - Mobility from related sectors
  - Mobility from unrelated sectors
  - Mobility from science system

Mobility from Same Sectors.

- Recruits from the same sector have a lower cognitive distance
  - Tend to have similar networks, work culture
  - Hold similar experience-based knowledge
  - Express this knowledge reflecting the conditions in the industry
  - Particularly so, when spatial boundaries apply (labor market regions)

- Pros
  - Assimilation of knowledge is easier
  - Lower absorptive capacity constraints
  - Lower risk of negative learning
- Cons
  - Lower level of novelty
  - Contribution to the retention / solidification of routines and practices (Madsen, et. al. 2003)

Mobility from Related Sectors.

- Mobility from related sectors
  - Cognitive distance
    - Not too close
    - Not too distant

- Tradeoff is required between (Nooteboom, 2000)
  - Cognitive distance – for the sake of novelty
  - Cognitive proximity – for the sake of more easy absorption

- Information is useless for the innovation process
  - If it is comprehendible by the firm but not novel to the firm
  - If it is novel to the firm but cannot be understood

Mobility from Unrelated Sectors.

- Mobility from fundamentally different domains has a high cognitive distance
  - Contribute dissimilar networks
  - Contribute diverse cultures
  - Provide insights in unrelated technologies
  - Have experience based knowledge that is novel to the firm

- Pros
  - High potential for innovation

- Cons
  - Absorptive capacity constraints
  - Risk of negative learning

Mobility from Science Sector.

- Mobility from science sector
  - Provides cutting edge technological knowledge
  - Routines that can benefit systematic R&D work
  - Provides ties to the scientific community
- Pros
  - High degree of novelty
  - Independent thinking and problem solving
- Cons
  - Distinctive culture and rationale of the science system might lead to absorptive capacity constraints

Research Question.

- Do aggregate labor mobility inflows affect the innovation performance of the firms?

- Inflows from
  - Same sector
  - Unrelated sectors
  - Related sectors
  - Science system

Filling a Gap.

- Previous research
  - finds strong evidence for labor mobility effects on firm / plant (productivity) performance
    Moens, 2003; Balsvik, 2011; Maliranta; 2009
  - finds strong evidence for inventor and scientist mobility effects on the inventive capacity of firms
    Agrawal, Cockburn, & McHale, 2006; Herrera, Munoz-Doyague, & Nieto, 2010; Oettl & Agrawal, 2008; Singh & Agrawal, 2011; Tzabbar, 2009
  - says little about labor mobility effects on commercial innovation

Recruiting.

- Recruiting is a generic core support process supplying the general workforce to the firm.

- We base our labor mobility flows on all of the firm's employees with a tertiary degree.

- Our approach to operationalize differs from some of the literature.
  - Not directly targeted to innovation activities (as in Andersson & Schubert, 2012)
  - Not specifically targeted to high potential or star scientists (as in Singh & Agrawal, 2011)
  - Not attracting inventors in general (as in Agrawal, Cockburn, & McHale, 2006)
  - Not explicitly intended to facilitate radical change / technological repositioning (Tzabbar, 2009)
  - Not focused on star creatives

Empirical Analysis:
Data, Method & Results.

Data.

- Mobility flows

  - Annual linked employer-employee data (2001-2005)
    - Links the employer to each employee in Norway (**all**)
    - Employer and employee can be identified by unique ID-numbers (**all**)
    - Labor mobility events can be identified

      change of the company ID attached to an employee
    - Additional characteristics can be merged

  - Samples from similar data sources have been used for the analysis of
    - firm demography

      (DK, FI, NO, SE) Nas et al. 2003; (FI) Ebersberger, 2011
    - knowledge spillover effects on firm productivity

      (NO) Balsvik 2011; (SE) Eriksson & Lindgren 2009; Boschma et al. 2009; (FI) Maliranta et al. 2009

Data.

- Innovation activities and innovation performance
  - Innovation Survey Data (2006-08)

  - Overall 3,197 observations from manufacturing, knowledge intensive services, aquaculture and extraction of petroleum and gas
  - 1,818 out of which are active in innovation activities
    - Positive innovation expenditure
    - Successful innovators
    - Abandoned or unfinished innovation projects

Measures.

- Dependent variables capture an innovation process
  - Stylized sequential model
  - Three stages

- Dependent variables (2006 – 08), all dichotomous
  - Innovation activities - dummy (ACTIVE)
  - Technological invention – patent applied, (INVENTION)
  - Innovation (INNOVATION)
    - Commercialized a new product (PRODUCT)
    - implemented a new process (PROCESS)

Measures.

- Independent variables: Mobility (2001-05)
  - From **same** NACE 5-digit sector (SAME)
  - From **related** sectors (RELATED)
  - From **unrelated** sectors (UNRELATED)
  - From **science & research** system (RESEARCH)

  - Definition of related / unrelated sectors as in Frenken et al. (2007) or Boschma et al. (2009)

- Control variables
  - Innovation activities (INNOVINT, COLLAB), firm demography (AGE, SIZE, GROUP, GROWTH, RESIDUAL), market access (MARBREADTH), 20 industrial sector dummies

Overview.

Table 1: Distribution of sample & output propensities by sector

Industry classification		Distribution of sample		Output propensities		
Sector classes	*Industry groups*	*All firms*	*Active firms*	INVENTION	PROCESS	PRODUCT
Low-tech manufacturing	Food & Beverages	8,5	8,1	6,1	42,6	62,8
	Textiles & Clothing	3,1	2,8	10,0	32,0	60,0
	Wood & furniture products	6,0	5,6	12,7	43,1	37,3
	Pulp & paper	1,1	1,0	11,1	61,1	44,4
	Publishing and printing	6,3	4,3	1,3	28,2	43,6
	Recycling	0,6	0,5	0,0	44,4	22,2
Low-medium tech manufacturing	Shipbuilding	4,5	4,0	26,4	40,3	51,4
	Transportation equipment	0,1	a)	a)	a)	a)
	Rubber & plastics	2,1	2,0	25,0	52,8	72,2
	Metals & minerals	10,9	9,2	14,3	44,0	50,0
	Manufacturing not included elsewhere	0,7	0,8	28,6	28,6	57,1
High medium-tech manufacturing	Machinery & instruments	11,1	13,3	34,7	32,6	63,6
	Automotive	1,7	1,6	24,1	34,5	58,6
	Chemicals	2,0	2,8	37,3	43,1	64,7
High-tech manufacturing	Electronics	1,3	1,9	28,6	45,7	62,9
	Pharmaceuticals	0,3	0,5	44,4	55,6	33,3
Knowledge intensive business services	New technology based business services	14,5	20,4	10,8	48,5	65,5
	Traditional professional business services	19,7	16,2	14,3	39,1	41,2
Natural resources	Aquaculture	1,9	1,8	0,0	43,8	25,0
	Extraction of petroleum & natural gas	3,6	3,2	27,6	25,9	29,3
Number of observations and sample averages		3197 (100 %)	1818 (100 %)	16,9	40,8	53,9

Note: Only industries represented in the CIS sample used. Output propensities is the percentage of active firms in the sector with the specified output. a) Statistics cannot be reported for groups containing less than 3 observations.

Methodology.

Dependent variable (ACTIVE)

- Probit regression
  - Independent variables
  - First order terms SAME, RELATED, UNRELATED, RESEARCH
  - Second order terms $SAME^2$, $RELATED^2$, $UNRELATED^2$, $RESEARCH^2$

- We report the marginal effects as derived in Ain & Norton (2003)

Methodology.

Dependent variable (INVENTION and INNOVATION)

- Bivariate probit regression
- Independent variables
  - First order terms SAME, RELATED, UNRELATED, RESEARCH
  - Second order terms $SAME^2$, $RELATED^2$, $UNRELATED^2$, $RESEARCH^2$

- Note: for probit models the marginal effects are not simply the parameter estimates.
  - We report the marginal effects as derived in Ain & Norton (2003)
  - Marginal effects of bivariate probit model with second order terms has to be derived building on Greene (1996) and Chrisofides et al (1997).

Marginal effects.

Bivariate probit regresion:

$$y_1^* = \alpha_1 z + \alpha_{11} z^2 + \beta_1 x + \epsilon_1$$

with

$$y_1 = 1 \quad \text{if} \quad y_1^* = 1,$$
$$y_1 = 0 \quad \text{otherwise}$$

and

$$y_2^* = \alpha_2 z + \alpha_{22} z^2 + \beta_2 x + \epsilon_2$$

with

$$y_1 = 1 \quad \text{if} \quad y_1^* = 1,$$
$$y_2 = 0 \quad \text{otherwise}$$

where $E(u_1) = E(u_2) = 0$, $Var(u_1) = Var(u_2) = 1$ and $Cov(u_1, u_2) = \rho$.

Marginal effects.

Quantities of interest:

Unconditional probability that y_1=1

$$\Pr(y_1 = 1|z,x) = \Pr(\epsilon_1 > -[\alpha_1 z + \alpha_{11} z^2 + \beta_1 x]|z,x) =$$
$$= \Phi(\alpha_1 z + \alpha_{11} z^2 + \beta_1 x) = \Phi(u_1) = \Phi_{1.1}$$

Unconditional probability of y_2=1

$$\Pr(y_2 = 1|z,x) = \Pr(\epsilon_2 > -[\alpha_2 z + \alpha_{22} z^2 + \beta_2 x]|z,x) =$$
$$= \Phi(\alpha_2 z + \alpha_{22} z^2 + \beta_2 x) = \Phi(u_2) = \Phi_{2.1}$$

Marginal effects.

Quantities of interest:

Probability that y_1=1 and y_2=1

$$\Pr(y_1 = 1, y_2 = 1|z, x) = \Phi[\alpha_1 z + \alpha_{11} z^2 + \beta_1 x, \alpha_2 z + \alpha_{22} z^2 + \beta_2 x, \rho] =$$
$$= \Phi(u_1, u_2, \rho) = \Phi_{1.1,2.1}$$

Probability that y_1=1 and y_2=0

$$\Pr(y_1 = 1, y_2 = 0|z, x) = \Phi[\alpha_1 z + \alpha_{11} z^2 + \beta_1 x, -(\alpha_2 z + \alpha_{22} z^2 + \beta_2 x), \rho] =$$
$$= \Phi(u_1, -u_2, \rho) = \Phi_{1.1,2.0}$$

Marginal effects.

Quantities of interest:

Conditional probability that y_1=1 conditional on y_2=1

$$\Pr(y_2 = 1|y_1 = 1|z, x) = \Phi[\alpha_2 z + \alpha_{22} z^2 + \beta_2 x - \rho(\alpha_1 z + \alpha_{11} z^2 + \beta_1 x)/(1 - \rho^2)^{0.5}] =$$
$$= \Phi\{(u_2 - \rho u_1)/(1 - \rho^2)^{0.5}\} = \Phi_{2.1|1.1}$$

Marginal effects.

Quantities of interest:

On the level of the probability density functions

$$\phi_{1.1} = \phi(u_1)$$
$$\phi_{1.0} = \phi(-u_1)$$
$$\phi_{2.1} = \phi(u_2)$$
$$\phi_{2.0} = \phi(-u_2)$$
$$\phi_{2.1|1.1} = \phi\{(u_2 - \rho u_1)/(1 - \rho^2)^{0.5}\}$$

Marginal effects.

Marginal effect of z on $\Phi_{1.1}$ is the univariate result (Christophides et al. 1997)

$$\frac{\partial \Phi_{1.1}}{\partial z} = \phi_{1.1} \cdot (\alpha_1 + 2\alpha_{11} z) =$$
$$\phi(\alpha_1 z + \alpha_{11} z^2 + \beta_1 x) \cdot (\alpha_1 + 2\alpha_{11} z)$$

Marginal effects.

For the marginal effect of z on $\Phi_{1.1,2.1}$ we note that
$\Phi_{1.1,2.1}=\Phi_{1.1} \cdot \Phi_{2.1,1.1}$

$$\frac{\partial \Phi_{1.1,2.1}}{\partial z} = \frac{\partial \Phi_{1.1} \cdot \Phi_{2.1|1.1}}{\partial z} =$$

$$= \frac{\partial \Phi_{1.1}}{\partial z} \cdot \Phi_{2.1|1.1} + \Phi_{1.1} \cdot \frac{\partial \Phi_{2.1|1.1}}{\partial z} =$$

$$= \phi_{1.1} \cdot \Phi_{2.1|1.1} + \Phi_{1.1} \cdot [\phi_{2.1|1.1} \cdot 1/(1-\rho^2)^{0.5} \cdot (\alpha_2 z + 2\alpha_{22} z - \rho \alpha_1 z - 2\rho \alpha_{11} z)]$$

$$= \phi(u_1) \cdot \Phi[(u_2 - \rho \cdot u_1)/(1-\rho^2)^{0.5}] +$$

$$+\Phi(u_1) \cdot \{\phi[(u_2 - \rho u_1)/(1-\rho^2)^{0.5}] \cdot 1/(1-\rho^2)^{0.5} \cdot (\alpha_2 z + 2\alpha_{22} z - \rho \alpha_1 z - 2\rho \alpha_{11} z)\}$$

Base line regressions.

Table A1: Baseline regression results. All observations

	Model 1	Model 2		Model 3	
Dependent variable:	ACTIVE	INVENTION	INNOVATION	PRODUCT	PROCESS
	Coefficient (SE)	*Coefficient (SE)*	*Coefficient (SE)*	*Coefficient (SE)*	*Coefficient (SE)*
Firm characteristics					
AGE	-0.121***	-0.148*	-0.055	-0.018	-0.052
	(0.044)	(0.079)	(0.057)	(0.057)	(0.055)
SIZE	0.211***	0.259***	-0.034	-0.018	-0.010
	(0.024)	(0.035)	(0.029)	(0.029)	(0.028)
GROUP	-0.006	0.240**	-0.025	0.066	-0.045
	(0.056)	(0.100)	(0.075)	(0.074)	(0.071)
GROWTH	-0.006	0.028	0.069	0.102**	0.030
	(0.037)	(0.063)	(0.051)	(0.049)	(0.047)
MARBREADTH	1.502***	0.989***	0.556***	0.761***	0.204
	(0.123)	(0.182)	(0.150)	(0.144)	(0.139)
Innovation strategy					
INNOVINT		0.217***	0.107***	0.158***	0.045**
		(0.026)	(0.027)	(0.027)	(0.022)
COLLAB		0.338***	0.368***	0.377***	0.385***
		(0.084)	(0.068)	(0.067)	(0.065)
Inflow intensities					
SAME	-2.719**	-0.350	-2.157	-0.738	-2.038
	(1.183)	(1.863)	(1.419)	(1.399)	(1.411)
SAME^2	5.512	2.369	5.731	1.791	4.895
	(3.833)	(6.211)	(4.589)	(4.486)	(4.488)
RELATED	3.062	3.009	3.744*	7.747***	1.962
	(1.949)	(2.954)	(2.260)	(2.282)	(2.172)
RELATED^2	-11.929	-20.508	-19.866*	-38.023***	-2.600
	(10.629)	(16.081)	(11.952)	(11.930)	(11.587)
UNRELATED	4.151***	2.251*	-0.054	0.931	-1.882**
	(0.726)	(1.248)	(0.922)	(0.921)	(0.886)
UNRELATED^2	-7.030***	-4.474	-0.320	-1.951	3.316
	(1.806)	(3.169)	(2.276)	(2.304)	(2.164)
RESEARCH	11.191***	17.106***	1.639	5.370	-5.851
	(3.858)	(5.172)	(4.059)	(4.139)	(3.891)
RESEARCH^2	-39.847	-130.573***	-49.788	-76.632**	12.043
	(30.939)	(43.414)	(31.403)	(32.933)	(30.270)
RESIDUAL	-0.206***	-0.047	-0.162*	-0.093	-0.009
	(0.057)	(0.312)	(0.088)	(0.178)	(0.082)
RESIDUAL^2	0.008***	-0.071	0.008**	-0.020	0.003
	(0.002)	(0.146)	(0.003)	(0.068)	(0.003)
Constant	-1.170***	-2.738***	-0.363	-1.239***	-0.608**
	(0.198)	(0.372)	(0.267)	(0.287)	(0.272)
Observations	3,197	1,818		1,818	
Walds Chi2 (df)	583.38 (34)***	4391.09 (72)***		1894.05(72)***	
Estimator	Probit	Bivariate probit			

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Estimations include 19 jointly significant industry dummies

Marginal effects.

Table 2: Regression results. Dependent variable: ACTIVE

	Model 1	
	Marg. Eff	*SE*
Firm characteristics		
AGE	-0,039	0,014***
SIZE	0,069	0,007***
GROUP	-0,002	0,018
GROWTH	-0,002	0,012
MARBREADTH	0,488	0,037***
Recruitment intensities		
SAME	-0,805	0,334**
RELATED	0,902	0,558
UNRELATED	1,082	0,174***
RESEARCH	3,526	1,173***
RESIDUAL	-0,064	0,018***

Note: N=3197. Average marginal effects and robust standard errors from probit regression Model 1, reported in Table A1 in the Appendix. . *** p<0.01, ** p<0.05, * p<0.1. The estimation include 19 jointly significant industry dummies.

Marginal effects.

Table 3: Regression results. Dependent variables: INVENTION and INNOVATION

	Model 2				Model 2					
	I INVENTION = 1		II INNOVATION = 1		III INVENTION = 1 & INNOVATION = 0		IV INVENTION = 0 & INNOVATION = 1		V INVENTION = 1 & INNOVATION = 1	
	Marg. Eff	*SE*	*Marg. Eff*	*SE*	*Marg. Eff*	*SE*	*Marg. Eff*	*SE*	*Marg. Eff*	*SE*
Firm characteristics										
AGE	-0,027	0,014*	-0,018	0,019	-0,004	0,004	0,005	0,019	-0,024	0,012**
SIZE	0,048	0,006***	-0,011	0,010	0,012	0,002***	-0,047	0,009***	0,036	0,005***
GROUP	0,044	0,018**	-0,008	0,025	0,011	0,005**	-0,042	0,025*	0,033	0,015**
GROWTH	0,005	0,012	0,023	0,017	-0,002	0,003	0,016	0,016	0,007	0,010
MARBREADTH	0,182	0,032***	0,187	0,050***	0,017	0,009**	0,022	0,047	0,165	0,027***
Innovation strategy										
INNOVINT	0,040	0,005***	0,036	0,009***	0,004	0,001***	0,000	0,008	0,035	0,004***
COLLAB	0,062	0,015***	0,124	0,022***	-0,001	0,004	0,060	0,022***	0,064	0,012***
Inflow intensities										
SAME	-0,040	0,287	-0,626	0,404	0,065	0,071	-0,521	0,391	-0,105	0,238
RELATED	0,432	0,457	1,048	0,649	-0,031	0,125	0,585	0,643	0,463	0,369
UNRELATED	0,288	0,151*	-0,033	0,217	0,068	0,041*	-0,253	0,219	0,220	0,121*
RESEARCH	2,715	0,808***	0,298	1,222	0,569	0,226**	-1,848	1,233	2,146	0,653***
RESIDUAL	-0,021	0,037	-0,052	0,028*	0,002	0,009	-0,029	0,037	-0,023	0,029

Note: N=1818. Average marginal effects and robust standard errors from bivariate probit regression Model 2, reported in Table A1 in the Appendix. .
*** p<0.01, ** p<0.05, * p<0.1. Estimations include 19 jointly significant industry dummies.

Marginal effects.

Table 4: Regression results. Dependent variables: PRODUCT and PROCESS

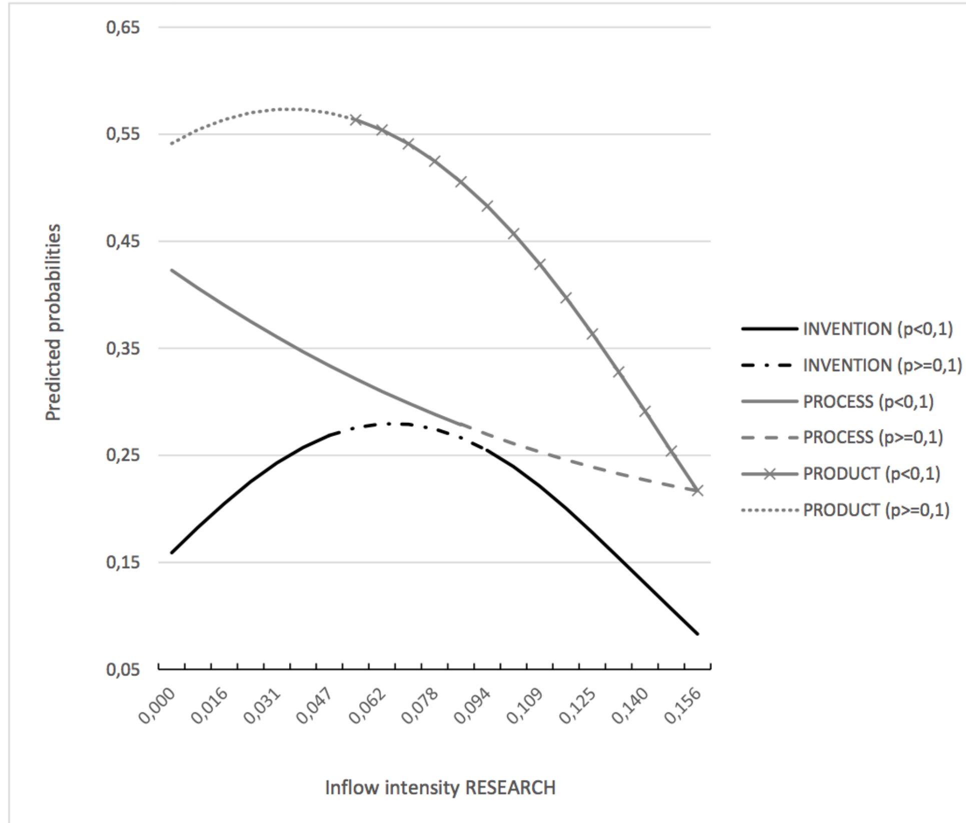
	Model 3				Model 3					
	I		II		III		IV		V	
	PRODUCT = 1		PROCESS = 1		PRODUCT = 1 & PROCESS = 0		PRODUCT = 0 & PROCESS = 1		PRODUCT = 1 & PROCESS = 1	
	Marg. Eff	*SE*	*Marg. Eff*	*SE*	*Marg. Eff*	*SE*	*Marg. Eff*	*SE*	*Marg. Eff*	*SE*
Firm characteristics										
AGE	-0,006	0,020	-0,019	0,020	0,007	0,015	-0,006	0,010	-0,014	0,015
SIZE	-0,006	0,010	-0,004	0,010	-0,002	0,007	0,001	0,005	-0,004	0,008
GROUP	0,023	0,026	-0,017	0,026	0,024	0,019	-0,016	0,013	-0,001	0,020
GROWTH	0,035	0,017**	0,011	0,017	0,015	0,012	-0,009	0,008	0,020	0,014
MARBREADTH	0,263	0,048***	0,075	0,051	0,118	0,037***	-0,069	0,025***	0,144	0,039***
Innovation strategy										
INNOVINT	0,054	0,009***	0,017	0,008**	0,024	0,006***	-0,014	0,004***	0,030	0,007***
COLLAB	0,130	0,022***	0,143	0,023***	-0,003	0,017	0,010	0,011	0,133	0,018***
Inflow intensities										
SAME	-0,224	0,413	-0,663	0,447	0,245	0,303	-0,194	0,211	-0,469	0,341
RELATED	2,267	0,671***	0,693	0,673	1,014	0,470	-0,561	0,326*	1,254	0,518**
UNRELATED	0,227	0,223	-0,520	0,228**	0,433	0,162	-0,314	0,119***	-0,206	0,172
RESEARCH	1,477	1,286	-2,097	1,280	2,115	0,886	-1,459	0,615**	-0,637	1,011
RESIDUAL	-0,039	0,042	-0,002	0,029	-0,023	0,028	0,014	0,018	-0,016	0,026

Note: N=1818. Average marginal effects and robust standard errors from bivariate probit regression Model 3, reported in Table A1 in the Appendix. .
*** p<0.01, ** p<0.05, * p<0.1. Estimations include 19 jointly significant industry dummies.

Findings.

- Mobility from science & research sector
  - Increases the likelihood to be innovation active
  - Affects invention (first positively then negatively)
  - Affects process innovation negatively
  - Affects product innovation negatively

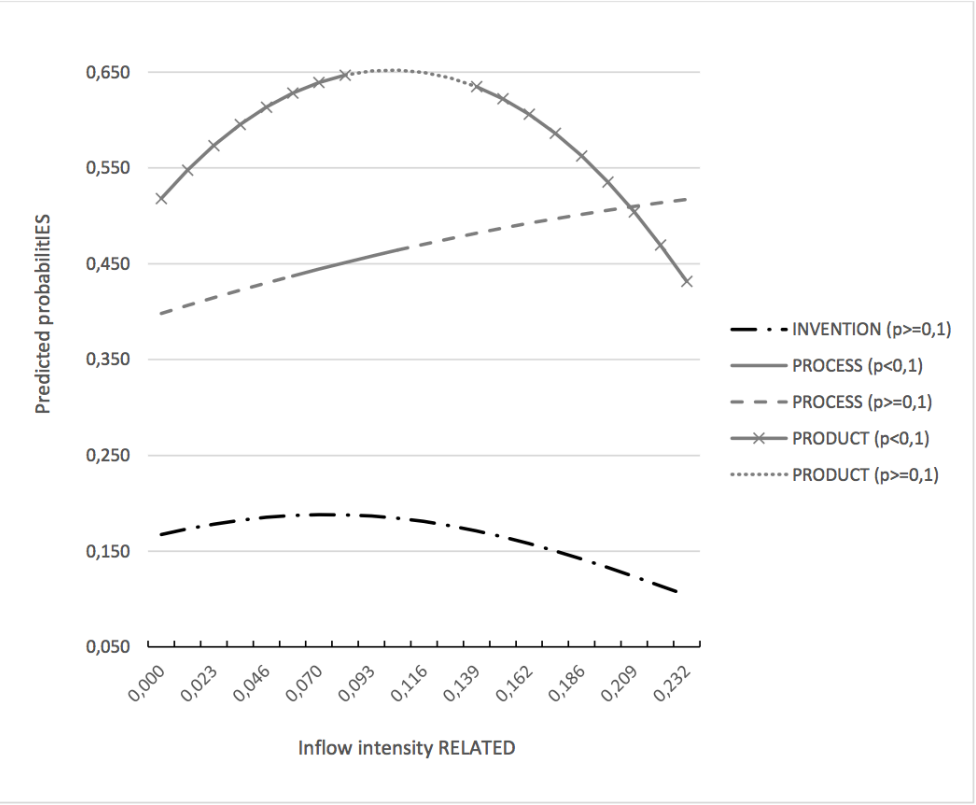
Figure 1: Predicted outcome probabilities and marginal effects (p < 0.1 | p >= 0.1) through the range of RESEARCH inflow



Findings.

- Mobility from related sectors
  - Has no effect on the likelihood to be innovation active
  - Affects product innovation in a non linear way
    - First positively
    - Then negatively
  - No effect on invention
  - Beyond the mean: positive effect on process innovation

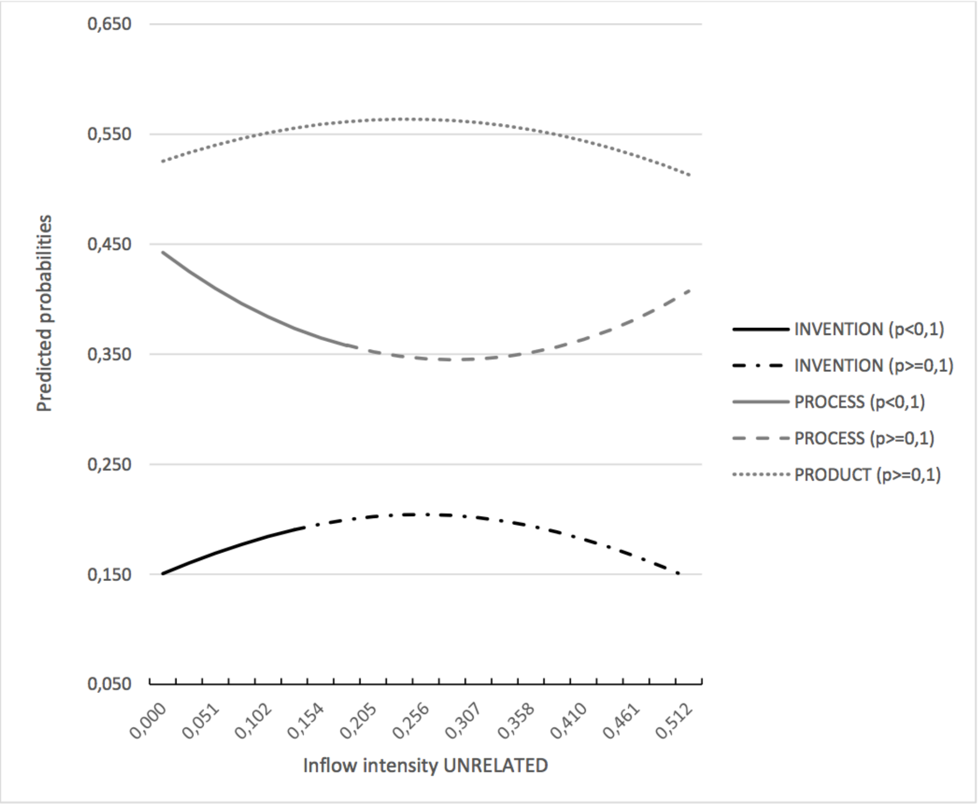
Figure 3: Predicted outcome probabilities and marginal effects (p < 0.1 / p >= 0.1) through the range of RELATED inflow.



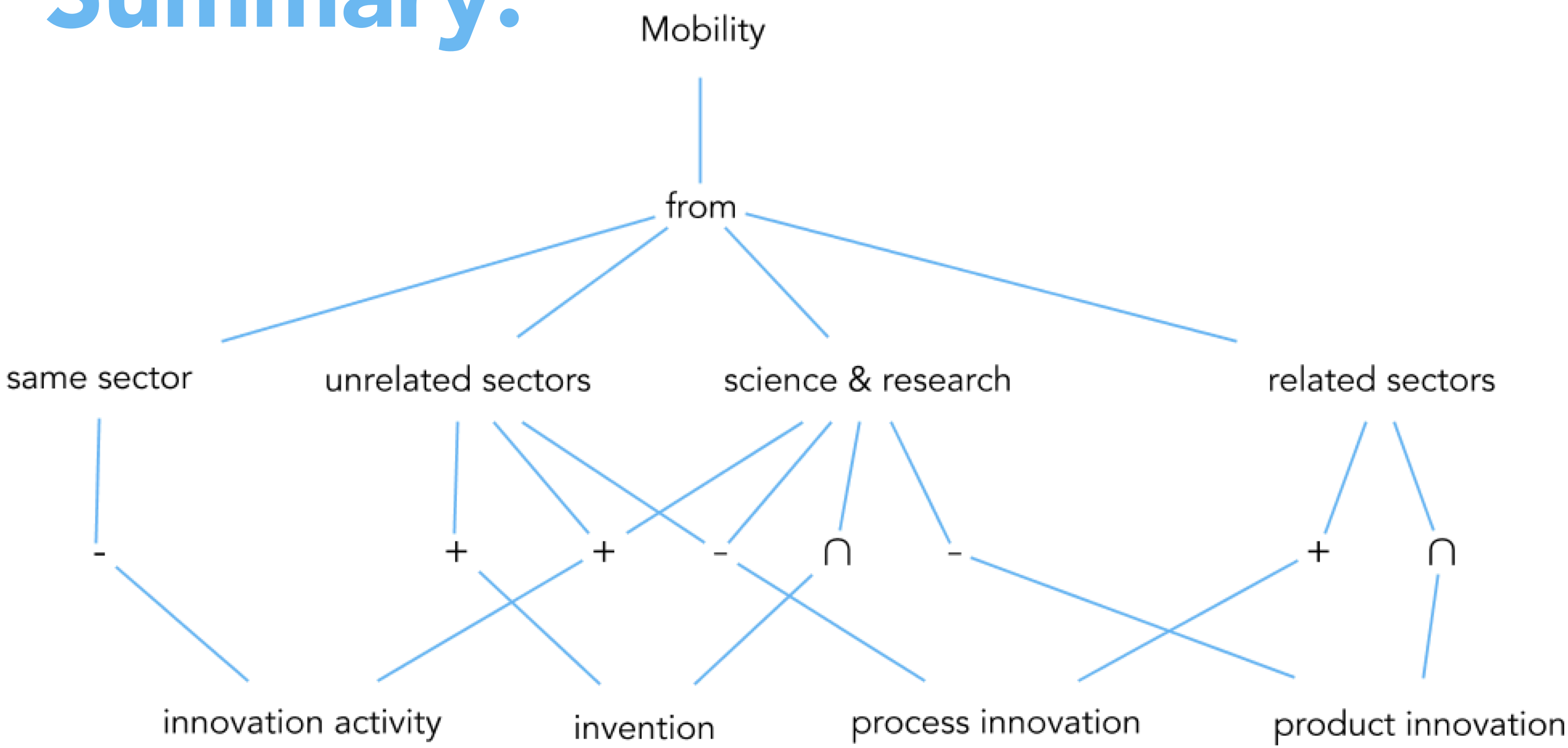
Findings.

- Mobility from unrelated sectors
  - Increases the likelihood to be innovation active
  - Increases technological invention
  - Decreases process innovation

Figure 2: Predicted outcome probabilities and marginal effects (p < 0.1 | p >= 0.1) through the range of UNRELATED inflow



Summary:



Mobility
from
same sector
unrelated sectors
science & research
related sectors
-
+
+
-
∩
-
+
∩
innovation activity
invention
process innovation
product innovation

Outlook.

- Role of MNEs – do employment flows from (Norwegian) MNEs matter?

- If network contacts (gone but not forgotten) matter then flows should not only matter
  - for the receiving firm (this research)
  - but also for the originating firm

- Current estimations depict only average effects
  - Effects on the whole distribution? – Quantile regression?
  - Dependent variables are dichotomous – Dichotomous quantile regression (Benoit & Van den Poel, 2012)


Recruiting affects innovation.
It matters where a firm's employees come from.

References.

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