Collected worker experiences and the novelty content of innovation

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Abstract

In this paper we investigate whether the novelty content of innovations introduced by Norwegian manufacturing firms reflect the composition of work-life experiences collected by employees. Distinguishing between ‘related’ (RV) and ‘unrelated’ (URV) variety and using employer-employee registers merged with Community Innovation Survey data to observe experiences prior to innovation strategies and results, we find the probability of incremental innovation increasing strongly with RV when firms are located in a large-city region. URV provide additional support for incremental innovation among firms that are not R&D active, and increases more generally the probability of radical (new-to-the world) innovation. However, these relationships flatten out at moderate levels, and the maximum impact of URV on radical innovation is limited compared to the average impact of firms’ R&D efforts. Thus, whereas incremental innovation is highly receptive to related worker experiences when collected and combined in urban contexts, radical innovation depend to a larger degree on the innovation strategies and efforts of the firm itself.

Key words: Human resources, innovation, related variety, unrelated variety, Norway

1. Introduction

Rapid rates of technology and market change combined with complexity of modern products and production processes entail that corporate innovation depends on a broader range of knowledge than resides with star scientists or can be contained within R&D departments and project groups (Grant 1996, Jensen et al. 2007, Parrilli and Alcalde Heras 2016, Castellacci et al. 2018). Classic contributions to organizational research and innovation studies (Lundvall and Johnson 1994, Nelson and Winter 1982, Arrow 1962, Nonaka 1994) emphasize that this knowledge to a large extent is the product of *experiences* gained as people progress through career paths shaped by the organizational labour markets of firms and the external labour markets of regions (cf. also Eriksson and Lindgren 2009, Power and Lundmark 2004). Taken together, this demands research attention to the collective dimension of innovation that is how people with different experiences interact 'in entire organizations' (Bell et al. 2011).

In line with this, the recent contribution by Östbring, Eriksson, and Lindgren (2018) focus on how the diversity of experiences 'collected' by employees influence the economic performance of employers. By doing so, it echoes prior research demonstrating that productivity respond to inflows of new employees when their experiences from other firms and industries are sufficiently different to represent a potential for learning yet similar enough for this potential to be captured (Timmermans and Boschma 2014, Boschma, Eriksson, and Lindgren 2009). However, the relationship between economic performance and innovation is complex (Crepon, Duguet, and Mairesse 1998b), and resources that support the former might not benefit the latter (Aarstad, Kvitastein, and Jakobsen 2016) that also come in many shapes and forms (Schumpeter 1934, OECD 2005). As research linking the diversity of human resources explicitly to different innovation output (cf. Østergaard, Timmermans, and Kristinsson 2011) has focused foremost on characteristics that are either given at birth (age, gender, ethnicity) or acquired very early in individuals' career paths (i.e. education, cf. also discussions in Bell et al. 2011, Horwitz 2005, Horwitz and Horwitz 2007), the elementary question of whether innovation reflects the diversity of *experiences* collected by employees remains open.

Here, we first discuss this question theoretically. Potential moderators of the relationship that are either internal to the firm (education levels, R&D) or external (location) are then identified, and hypotheses are developed to guide the subsequent empirical analysis using a unique dataset comprised of linked innovation and employment register data for almost 1500 Norwegian manufacturing firms.

2. Collected worker experiences and innovation

The constituent components of innovative capability is knowledge embodied in organizational members (Nelson and Winter 1982, Nonaka 1994), the routines through which they are mobilized and integrated (Kogut and Zander 1992, Cyert and March 1963) and the contact points maintained with the external environment (Laursen and Salter 2006). As individuals move through the labour market, they acquire skills (Timmermans and Boschma 2014), establish acquaintances (Bouty 2000, Agrawal, Cockburn, and McHale 2006) and develop behavioural attributes (Dokko, Wilk, and Rothbard 2009) that reflect what they do, how they do it and who they encounter.

Accordingly, experiences collected by employees might influence innovative capability at heart (Herstad, Sandven, and Ebersberger 2015). The ‘cognitive resource diversity theory’ applied in human resource research (cf. Horwitz 2005) proposes that firms benefit from diverse experiences because they represents a range of knowledge and ideas, networks and perspectives that triggers learning and facilitates innovation through ‘new combinations’ (Van Engen and Van Woerkom 2010, 133). Moreover, a diverse workforce brings in different social and professional networks (Bouty 2000, Agrawal, Cockburn, and McHale 2006), and equals broader ‘prior related knowledge’ that might increase the ability to identify, assimilate and exploit external knowledge (Cohen and Levinthal 1990). This may be particularly beneficial for original and boundary-crossing recombination of knowledge (Bantel and Jackson 1989, van Knippenberg, De Dreu, and Homan 2004, Carlile 2004) because it challenges group-think and assist avoiding lock-in (Phillips, Liljenquist, and Neale 2009, Schuetz 1944).

On the other hand, the ‘similarity attraction paradigm’ (cf. Horwitz 2005, Horwitz and Horwitz 2007) argues that people prefer to work with others that they perceive as similar. Due to more effective communication and less divergent perspectives, similarity might enhance the execution of tasks and provide the basis for continuous incremental improvements of products and practices (March 1991). This, however, comes with the risk of ‘myopia’ prohibitive of more fundamental changes (Levinthal and March 1993). Very diverse attributes, on the other hand, could lead to distrust, a lack of shared understanding and a high risk of conflicts that may also reinforce the firm’s focus on retaining rather than adjusting established products and practices (Horwitz 2005, Jehn, Northcraft, and Neale 1999, Madsen, Mosakowski, and Zaheer 2003).

Therefore, diversity has been depicted as a 'mixed blessing' (Williams and O'Reilly 1998) or a 'two-edged-sword' (Milliken and Martins 1996, cf. also Basset-Jones 2005). This has led to a substantial volume of research that is concerned with how employee diversity along dimensions such as age, gender, ethnicity and education affects firm performance (van Knippenberg, De Dreu, and Homan 2004, Kearney, Gebert, and Voelpel 2009, Horwitz and Horwitz 2007, van Knippenberg and Schippers 2007) and innovation (Mohammadi, Broström, and Franzoni 2017, Bogers, Foss, and Lyngsie 2018, Østergaard, Timmermans, and Kristinsson 2011). We extend this by examining first whether *experiences* described in the dimension similarity-diversity *per se* influences the novelty content of innovation (Nooteboom 2000, Solheim and Herstad 2018) and do so under the assumption that broader experiences translate into a larger potential for truly new products and practices:

H1a. Intra-firm variety of collected experiences is positively associated with radical innovation

H1b. Intra-firm variety of collected experiences is negatively associated with incremental innovation

However, it might be that it is not diversity per se that matters for innovation, but rather the kind of diversity. Concepts such as 'cognitive complementarity' (Nooteboom et al. 2007) and 'relatedness' (Boschma 2017) are used in the literature to underscore that agents must have something in common in order for the learning potential associated with differences in perspectives to be captured. Thus, Frenken, Van Oort, and Verburg (2007) argue that if variety is to support innovation, it must be related, that is, cognitively close, yet not similar. Recent studies at the regional level suggest that 'related variety' enhances incremental innovations, while unrelated variety is more conducive to radical innovation (Castaldi, Frenken, and Los 2015, Miguelez and Moreno 2018). Firm-level studies of collected experiences are more recent (Östbring, Eriksson, and Lindgren 2018), and include Solheim and Herstad (2018) who follow March (1991) in suggesting that the differences in perspectives associated with *unrelated variety* (URV) might be particularly important for explorative organizational learning while *related variety* (RV) support exploitation expressed as streams of incremental changes. This is reflected in two hypotheses capturing different relationships between innovation and experience variety:

H2a: Intra-firm related variety of collected experiences is positively associated with incremental innovation

H2b: Intra-firm unrelated variety of collected experiences is positively associated with radical innovation

Several moderators of the relationship between variety and innovation might be at play. On the one hand, education may strengthen the capacity of individuals to accumulate, interpret and convey experience-based knowledge between different contexts of application (Nelson and Phelps 1966, Herstad, Sandven, and Ebersberger 2015), and communicate effectively in new organizational settings, meaning it should strengthen the relationships predicted in Hypothesis 2a and 2b. On the other, education and experience may be substitutive, meaning the importance of either one increases as the other decreases. Acknowledging this, Östbring, Eriksson, and Lindgren (2018) emphasize the multi-dimensional nature of human cognitions and find that education dampens the negative effect of experience similarity on the productivity performance of Swedish services firms. This gives rise to a first hypothesis on moderating effects:

H3: The relationship between experience variety and innovation depend on the education level of staff

The relationship between human resource diversity and innovation might also depend on firms' innovation strategies and commitment to development work, as can be approximated here by whether or not they engage themselves in R&D. In-house R&D may on the one hand increase the capacity of firms to integrate and exploit broad internal and external resources (Teece 2009, Cohen and Levinthal 1989). On the other hand, internal variety might be more important in the absence of R&D when firms organize their development work as an integral part of daily business operations (Jensen et al. 2007). A strong emphasis on R&D might even reduce the receptiveness of firms to ideas and knowledge from their broader organizations (cf. the discussion of R&D and the 'not-invented-here' syndrome in Laursen and Salter 2006). A second hypothesis on moderating effects is therefore formulated:

H4: The relationship between experience variety and innovation depend on whether firms engage in in-house R&D

Finally, the limited spatial mobility of labour entail that the relationships hypothesized in 2a and 2b might be influenced by the characteristics of *regions* in which firms have evolved or chosen to locate. In line with the recent study by Eriksson and Rodríguez-Pose (2017) where plants in metropolitan areas where found to capture the largest productivity benefits from labour market mobility, we approximate locations here by drawing on literature suggesting that cities are hot-spots for innovation because they contain diverse knowledge resources with a high connectivity to the outside world (Glaeser 2011, Glaeser et al. 1992, Jacobs 1969) and labour markets that facilitate the continuous matching of diverse employee skills with different employer needs and innovation ambitions (Duranton and Puga 2004, Andini et al. 2013, Almeida and Kogut 1999).

This suggests that the relationship between intra-firm URV and radical innovation predicted in Hypothesis 2b might be stronger when firms have located in a large-city region and accumulate high URV that also provides broad contact points to the surrounding economy and absorptive capacity to match diverse external information and resources. Firms may also locate in cities to benefit from local labour markets that link similar or different-yet-related local industries (Frenken, Oort, and Verburg 2007, Jøranli and Herstad 2017) and serve as point of gravitation in flows of specialised skills occurring at larger geographical scale. In line with Lee and Rodríguez-Pose (2013) who found location in UK cities associated with higher probabilities of innovation by imitation, this suggests that RV accumulated by firms in cities is particularly supportive of incremental innovation as predicted in Hypothesis 2a.

However, learning-by-recruiting and uncontrolled spillovers associated with job-hopping in urban contexts may reduce the emphasis of firms on own innovation efforts (Herstad 2018b), meaning that the relationship predicted in Hypothesis 2b might become less pronounced, even absent. In extension, firms located outside urban regions may develop broader extra-regional network ties (e.g. Isaksen (2015), Grillitsch and Nilsson (2015)) and invest more in their internal human resources (Eriksson and Rodríguez-Pose 2017) to compensate for external resource constraints. Thus, as was the case for Hypotheses H3 (interactions between education and collected experience) and H4 (interaction between R&D collected experiences), we can only suggest that moderating effects of location might be at play and leave their nature open for the empirical analysis to explore:

H5: The relationship between experience variety and innovation depend on whether firms are located in a large-city region

3. Data, variables and estimation strategy

3.1. Data

We use innovation data sampled by Statistics Norway in the Seventh round of the Pan-European Community Innovation Survey (CIS2010) that is based on the definitions and guidelines of the Oslo Manual (OECD 2005). The 2010 survey provides information on innovation activities and outcomes during the reference period 2008–2010, for firms with 5–9 employees (restricted survey with limited information) and 10 employees or more (full survey). Prior to release for research purposes, the data were thoroughly reviewed and validated by Statistics Norway. To provide information on collected experiences, the data have been merged with Linked Employer-Employee Data (LEED) covering the years 2004–2008 (see section on 'collected experiences' below).

The linked CIS-LEED dataset consists of 6,595 enterprises in manufacturing (including offshore oil & gas) and various services industries, of which 5,402 had 10 employees or more in 2010. Only such firms were asked to provide information on novelty content. Of these, we excluded 3,750 enterprises belonging to wholesale trade and logistics, hotels, restaurants and catering, infrastructure and knowledge intensive services industries. This is due to the total absence of radical innovation (as defined here) in several sub-sector of services and extensive 'missing' information on novelty content more generally indicating that the CIS poorly captures this dimension of innovation in services (Nordli 2016, Toivonen and Tuominen 2009).

Of the remaining 1,652 enterprises in manufacturing industries, 81 were established after 2008, and excluded due to missing information on collected employee experiences at the beginning of the CIS reference period (cf. 'independent variables' below). Finally, 92 firms established in 2006-2008 were excluded because the required controls for labour replacement rates in this period could not be computed (cf. 'control variables' below). Consequently, the sample used consists of the 1,463 enterprises for which descriptive statistics are provided in Table A1 in The Appendix.

3.2. Dependent variables

In the survey, respondents were asked to evaluate the novelty content of product and process innovations. Compared to process innovations, the externally oriented nature of product innovation means that respondent assessments are more reliable. Thus, the variable INCREMENTAL takes on the value 1 when product innovations are reported as new to the firm's market, but not to the world market, meaning that firms introduced onto their own market a product already offered on other (geographical or sectoral) markets. The variable RADICAL takes on the value 1 if the firm reported introducing a product that was new to the firm itself, its market and to the world.

3.3. Collected experiences

The main independent variables used in the analysis capture the composition of 'experience years' collected by firms' entire staff at the start of the three-year period for which innovation output is reported, i.e. in 2008. Based on LEED, matrixes have been generated for each firm that uses industry codes to classify the prior workplaces of employees (Table 1). This demands that industry classifications are consistent over time. Yet, standards have changed substantially over the years and entirely new classes have been added. As a result, we focus on the most recent experiences, i.e. those collected during the five-year period 2004-2008 for which the data allow to harmonize the previous SN2002 classification standard (building on NACE Rev. 1.1) with the current SN2007 (building on NACE Rev. 2).

Based on these matrixes, we describe how the experiences of individual employees are related to *each other* using entropy measures computed in accordance with Jaquemin and Berry (1979) as detailed in the Appendix. Unrelated variety (denoted URV) captures the distribution of experience-years *across* two-digit main industry groups. Related variety (RV) is the weighted sum of experience-year distributions at the 3-digit level *within* 2-digit main groups, where the weight is the proportion of all experience-years that each 2-digit group account for. Finally, Total Variety (denoted TV) is the sum of URV and RV. This operationalisation of RV and URV is as originally proposed by Frenken, Oort, and Verburg (2007) and later applied e.g. in Boschma, Eriksson, and Lindgren (2009). In the regressions, the actual entropy measures reported in Table A1 in the Appendix have been standardized to allow straightforward computation of marginal effects. This simply means that they have been rescaled to standard deviations above or below the full sample mean that is set to 0 by the procedure (cf. Table A2 in the Appendix).

To illustrate, Table 1 gives an example of a firm that had 20 employees in 2008 and was engaged in the manufacture of engines and turbines (NACE 28.110). Including 2008 and the four years prior to it yields 20 x 5 = 100 experience-years, of which 74 were associated with employment in the focal firm's sector (NACE 28.110) and a minimum of 20 in the firm itself. Due to unemployment, five person-years do not count as experience-years. The remaining 21 experience-years were generated in NACE 09.101 (oil & gas sector drilling services), NACE 24.421 (primary production of aluminium), NACE 24.422 (aluminium semi-finished products), NACE 26.110 (electronic components), NACE 26.200 (computers and equipment), NACE 26.300 (communication equipment) and NACE 62.020 (programming services).

Table 1: Example of experience diversity matrix. Firm with 20 employees.

Year of observation		**Sector of employment in prior years**			
Employee no.	**2008**	**2007**	**2006**	**2005**	**2004**
1	28.110	09.101	09.101	09.101	09.101
2	28.110	28.110	28.110	28.110	28.110
3	28.110	28.110	62.020	62.020	62.020
4	28.110	28.110	28.110	28.110	28.110
5	28.110	28.110	28.110	28.110	28.110
6	28.110	28.110	*unemployed*	*unemployed*	*Unemployed*
7	28.110	28.110	28.110	28.110	28.110
8	28.110	28.110	28.110	62.020	62.020
9	28.110	28.110	28.110	28.110	28.110
10	28.110	28.110	28.110	28.110	28.110
11	28.110	28.110	28.110	28.110	28.110
12	28.110	28.110	28.110	*unemployed*	*Unemployed*
13	28.110	28.110	28.110	28.110	28.110
14	28.110	28.110	28.110	28.110	28.110
15	28.110	28.110	24.421	24.421	24.421
16	28.110	24.422	24.422	24.422	24.422
17	28.110	28.110	28.110	26.110	26.200
18	28.110	28.110	28.110	28.110	28.110
19	28.110	28.110	26.300	26.300	26.300
20	28.110	28.110	28.110	28.110	28.110
Unrelated experience diversity (Entropy of distribution between 2-digit groups)					0.830069
+ Related experience diversity (Entropy of distribution within 2-digit groups)					0.100334
= Total experience diversity (Entropy of distribution between 5-digit groups					0.930403

3.4. *Control variables*

Location choices, experiences and innovation propensities differ between industry groups. Therefore, 21 dummy variables are included in all regressions as controls for 22 two-digit industry groups (cf. Table A1). Variety measured as entropy is influenced by the size of the firm and may also be related to age. As both may influence innovation, the logs of firm age (AGE) and size (SIZE) are included as controls. Experience variety is also related to the labour replacement rates of firms, as stability of staff inherently translates into low experience variety hypothesized to negatively influence innovation. However, stability per se may positively influence innovation (Kleinknecht, van Schaik, and Zhou 2014, Zhou, Dekker, and Kleinknecht 2011). This demands that the (assumed positive) effect of experience variety is isolated from the (potentially negative) effect of labour replacement. Therefore, the control variable CHURN is included that captures the proportion of employees present in the firm in 2006 that was replaced in the two-year period that ended at the start of the CIS reference period in 2008. Foreign market presence provides incentives to innovate due to competitive pressure and market size (Crepon, Duguet, and Mairesse 1998a, Ebersberger and Herstad 2012), and influences the ability of respondents to evaluate whether a product is new to the world market. Foreign market presence is captured by the variable FORMAR.

The variable EDUL is the average education level of firms' employees in 2008, described on the standard eight-level scale used in the registers. The variable is included to isolate effects of education and estimate interaction effects in accordance with Hypothesis H3. Similarly, the variable R&D takes on the value 1 for firms that stated in the CIS that they engaged in own (internal) research and development activities during the reference period. It is included to isolate effects of such efforts on innovation and estimate interaction effects in accordance with Hypothesis H4.

Finally, the variable URBAN captures location in a large-city region. Prior research has used commuting patterns to develop (Jukvam 2002) and update (Gundersen and Jukvam 2013) a classification consisting of 161 Norwegian 'housing and labour market regions' that are ranked on a centrality scale from 5 (The capital labour market region) through 4 (other large-city labour market regions) to 1 (peripheral regions). URBAN takes on value 1 for firms located at centrality level 4 (Bergen, Stavanger, Trondheim) and 5 (The Capital). Because the CIS is sampled at the enterprise level and enterprises may consist of several establishments in different regions, multi-establishment enterprises have been assigned to the single regions that accounted for their largest shares of employment (see section on multicollinearity and robustness).

3.5. Estimation strategy

The two binary dependent variables are estimated separately in probit regressions where independent variables are added step-wise to evaluate model fit. As the variables describing collected experiences are continuous, it is necessary to consider whether curvilinear effects are at play that may influence estimates for variety as well as the significance of interactions as predicted in hypotheses H3, H4 and H5 (Ganzach 1997)[1]. In line with Haans, Pieters, and He (2016), the models include interactions involving the base variety terms and the squared variety terms. This introduces a distinction between the independent *variable* of interest (i.e. RV or URV) and the multiple *terms* used to describe it (e.g. the base term, the squared term and interactions involving the base term and the squared term). As it is the significance of the *variable* that is of substantive interest, supplementary Wald's tests are used to evaluate joint significance (of all terms) and the results are used to ascertain what the appropriate model specifications are for each of the dependent variables.

Similarly, to interpret the actual impact of a variable on innovation, it is necessary to calculate marginal effects (Hoetker 2007). Single 'on average' marginal effect estimates are of limited interest when polynomial and interaction terms are involved, as the sign, size and significance vary through the range of values on the independent variable. Therefore, predicted probabilities and marginal effects of each variety variable have been computed for a range that span from their approximate minimum values through the mean and up to the cut-point value for the 95th percentile of each variety distribution. All other variables are held constant at their mean effects.

[1] Ganzach (1997) argues that failure to include squared terms when the underlying relationship is curvilinear may lead to 'false' interactions being detected.

4. Results

4.1. Incremental innovation

Table 2 displays the baseline estimations of INCREMENTAL. Estimates for R&D are significantly positive, while estimates for FORMAR are significantly negative. The latter suggest that innovation pressures and inspiration coming from international markets draws the attention of the firm away from incremental innovative efforts. Moreover, the estimate for CHURN is positively significant in Model 2 but turns insignificant once curvilinear effects of RV and URV are accounted for in Model 3. This is a first indication that labour market processes provide support for incremental innovation.

The estimate for TV in Model 1 is insignificant, giving no support for Hypothesis 1b that predicted a negative relationship. Model 2 distinguishes between RV and URV, obtaining positive estimates for the former that are supportive of Hypotheses 2a. Model 3 reveal that the effect of URV is curvilinear and takes on an inverted U-shape form, as the squared term is significantly negative. Supplementary Wald's tests reported at the bottom of the Table reveal that the two terms capturing each of the variables RV and URV are jointly significant even though they in the case of RV are not individually significant.

Model 4 considers interaction effects between experience variety and education. No significant interaction effects are found, and variety is barely significant when individual terms are tested jointly. By contrast, a significant negative interaction between R&D and URV is detected in Model 5. In Model 6 that considers interactions between variety and location, the joint significance of all terms capturing RV is strong[2] while the joint significance of all terms capturing URV is reduced compared to Model 4. Thus, we conclude that the best fit is Model 7 that account for interactions between RV and location (but not education or R&D) and interactions between URV and R&D (but not location or education).

[2] In supplementary estimations not reported where only interactions between URBAN and the linear variety terms are included, the interaction between RV and location is strongly significant.

Table 2: Baseline regression results, product innovation new to the firm's market but not the world.

	Dependent variable: INCREMENTAL						
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
	Coeff	*Coeff*	*Coeff*	*Coeff*	*Coeff*	*Coeff*	*Coeff*
	(se)	*(se)*	*(se)*	*(se)*	*(se)*	*(se)*	*(se)*
AGE (log)	-0.097	-0.091	-0.093	-0.093	-0.095	-0.103	-0.104
	(0.082)	(0.082)	(0.083)	(0.083)	(0.083)	(0.083)	(0.084)
SIZE (log)	-0.039	-0.050	-0.063	-0.061	-0.063	-0.063	-0.064
	(0.046)	(0.046)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)
R&D	1.145***	1.155***	1.160***	1.156***	1.156***	1.161***	1.158***
	(0.105)	(0.105)	(0.106)	(0.106)	(0.131)	(0.106)	(0.125)
FORMAR	-0.821***	-0.837***	-0.827***	-0.819***	-0.825***	-0.823***	-0.817***
	(0.138)	(0.139)	(0.140)	(0.140)	(0.140)	(0.140)	(0.140)
EDUL	-0.065	-0.051	-0.046	-0.016	-0.043	-0.052	-0.047
	(0.084)	(0.084)	(0.085)	(0.109)	(0.086)	(0.086)	(0.086)
CHURN	0.519	0.686*	0.470	0.504	0.482	0.449	0.439
	(0.408)	(0.415)	(0.430)	(0.437)	(0.434)	(0.435)	(0.436)
URBAN	0.065	0.054	0.062	0.065	0.070	0.142	0.054
	(0.102)	(0.102)	(0.103)	(0.103)	(0.104)	(0.132)	(0.111)
TV	0.006						
	(0.053)						
RV		0.145***	0.085	0.209	0.045	0.009	-0.017
		(0.048)	(0.077)	(0.431)	(0.109)	(0.093)	(0.093)
RV^2			0.021	-0.080	0.024	0.024	0.028
			(0.022)	(0.168)	(0.032)	(0.026)	(0.026)
URV		-0.095*	-0.019	0.009	0.164*	-0.055	0.156*
		(0.057)	(0.066)	(0.343)	(0.095)	(0.075)	(0.092)
URV^2			-0.098**	0.119	-0.082	-0.058	-0.079
			(0.041)	(0.244)	(0.063)	(0.048)	(0.064)
EDUL*RV				-0.034			
				(0.117)			
EDUL*RV^2				0.027			
				(0.046)			
EDUL*URV				-0.005			
				(0.094)			
EDUL*URV^2				-0.056			
				(0.065)			
R&D*RV					0.048		
					(0.147)		
R&D*RV^2					-0.001		
					(0.044)		
R&D*URV					-0.316***		-0.299***
					(0.118)		(0.111)
R&D*URV^2					0.000		-0.000
					(0.082)		(0.083)
URBAN*RV						0.204	0.242*
						(0.153)	(0.143)
URBAN*RV^2						-0.010	-0.018
						(0.046)	(0.044)
URBAN*URV						0.143	
						(0.129)	
URBAN*URV^2						-0.127	
						(0.090)	
Constant	0.006	-0.829*	-0.660	-0.786	.0.667	-0.644	-0.616
	(0.053)	(0.429)	(0.444)	(0.512)	(0.448)	(0.448)	(0.450)
Wald Chi2 tests of joint coefficient significance							
All terms involving RV			9.48***	9.41*	8.21*	11.80**	12.57**
All terms involving URV			7.01**	6.81	13.88***	8.33*	13.51***
Observations	1463	1463	1463	1463	1463	1463	1463
LR Chi2 (df)	207.71(27)	217.71(28)	224.97(30)	226.43(34)	233.36(34)	232.08(34)	237.71(34)
R2	0.1768	0.1853	0.1915	0.1928	0.1987	0.1976	0.204

Note: Probit regressions. ***, ** and * indicate significance at the 1 per cent, 5 per cent and 10 per cent levels respectively.
All models are significant at $p < 0.01$

Table 3 reports predicted probabilities of INCREMENTAL and the marginal effects associated with RV when URBAN = 1 and URBAN = 0 and the effect of all other variables including URV are held constant at their respective means. When firms are located in a large-city region (URBAN=1), increases in RV give rise to increases in the probability of innovation that are significant once RV reaches the relatively moderate level of 0.2 standard deviations below the mean value for RV in the full sample. Through the range in which marginal effects are significant, the predicted probability of INCREMENTAL increases by 12.9 percentage-points, meaning it more than doubles. Throughout the whole range of observed RV, it increases by 15 percentage points. This effect is of substantial size even compared to the estimated effect of R&D activity that is 18.5 percentage-points[3] when all other variables are held constant at the mean. Outside large-city regions, the predicated probability remains stable as RV changes. Combined, this gives rise to significant urban-rural dividing lines in innovation propensities when urban firms with RV above 1 SD are compared to rural firms[4].

Table 3: Predicted probabilities (PP) and marginal effects (ME) of related variety (RV) and location (URBAN) on INCREMENTAL). Computed from Model 7 (N=1463). 0 = mean diversity observed in the full sample

RV	**URBAN = 1**			**URBAN = 0**		
SD from mean	PP	ME	SE	PP	ME	SE
-0.8	0.081	0.031	0.022	0.109	-0.012	0.025
-0.4	0.095	0.037	0.023	0.105	-0.007	0.020
-0.2	0.102	0.039	0.024*	0.104	-0.005	0.018
0 (mean)	0.110	0.042	0.024*	0.103	-0.003	0.017
0.2	0.119	0.046	0.024*	0.102	-0.001	0.015
0.4	0.129	0.049	0.024**	0.102	0.001	0.014
0.6	0.139	0.052	0.025**	0.103	0.003	0.013
0.8	0.150	0.056	0.025**	0.103	0.005	0.013
1	0.161	0.060	0.025**	0.105	0.007	0.012
1.2	0.174	0.064	0.026**	0.106	0.009	0.012
1.4	0.187	0.068	0.027**	0.108	0.011	0.013
1.6	0.201	0.072	0.029**	0.111	0.014	0.014
1.8	0.216	0.076	0.031**	0.114	0.016	0.015
2	0.231	0.081	0.034**	0.117	0.019	0.016

Note: Predicted probabilities and marginal effects of diversity and location computed at the mean effect of all other variables.

This, however, is not the full picture for INCREMENTAL. Holding RV constant at 0 SD (full sample mean) and allowing URV to vary across the range of values while accounting for the significant interaction with R&D, Table 4 demonstrate that increases from low to moderate levels of URV are associated with increases in the probability of INCREMENTAL among firms that are not R&D active. Once firms are engaged, URV has the diametrically opposing effect

[3]Supplementary marginal effect estimations not reported. Significance at the 10 per cent level or stronger. All other variables held constant at their mean effects.
[4] See footnote 3.

of reducing the probability of incremental innovation once it reaches moderate to high levels. This suggests that URV draws the attention of R&D-active firms away from incremental changes towards the more ambitious efforts that we now turn to consider.

Table 4: Predicted probabilities (PP) and marginal effects (ME) of unrelated experience variety (URV) on INCREMENTAL. Computed from Model 7 (N=1463). 0= mean diversity observed in the full sample.

URV	**R&D = 1**			**R&D = 0**		
SD from mean	PP	ME	SE	PP	ME	SE
-1.6	0.247	0.033	0.062	0.020	0.026	0.008***
-1.4	0.253	0.024	0.058	0.024	0.028	0.011***
-1.2	0.257	0.015	0.053	0.028	0.029	0.012**
-1	0.259	0.005	0.048	0.033	0.029	0.014**
-0.8	0.259	-0.005	0.043	0.037	0.029	0.014**
-0.6	0.257	-0.014	0.037	0.042	0.027	0.014*
-0.4	0.253	-0.024	0.032	0.046	0.026	0.014*
-0.2	0.247	-0.033	0.028	0.051	0.023	0.013*
0 (mean)	0.239	-0.042	0.024*	0.054	0.020	0.013
0.2	0.229	-0.050	0.022**	0.057	0.017	0.012
0.4	0.218	-0.058	0.021***	0.060	0.013	0.013
0.6	0.205	-0.065	0.022***	0.062	0.009	0.015
0.8	0.191	-0.072	0.024***	0.063	0.004	0.017
1	0.176	-0.077	0.026***	0.063	0.000	0.019
1.2	0.160	-0.082	0.028***	0.063	-0.005	0.021
1.4	0.143	-0.085	0.029***	0.062	-0.009	0.023
1.6	0.127	-0.087	0.029***	0.060	-0.013	0.025
1.8	0.110	-0.087	0.028***	0.057	-0.017	0.026
2	0.080	-0.047	0.023**	0.042	-0.012	0.008

Note: Predicted probabilities and marginal effects of diversity and location computed at the mean effect of all other variables.

4.2. Radical innovation

Table 5 report baseline estimations for RADICAL. Compared to the negative estimate obtained for FORMAR in the regressions on INCREMENTAL, it is notable that the association here is positive and significant in all model specifications. Moreover, while EDUL did not yield significant estimates for INCREMENTAL, the relationship is here positive and strongly significant, as is the estimate for R&D. Estimates for CHURN are significantly negative in all but the two first models, suggesting that labour replacement *per se* reduces the probability of radical innovation.

TV is insignificant in the baseline Model 8. In Model 9, positive estimates are obtained only for URV. When squared terms are included in Model 10, both base and squared terms for URV are significant. The terms capturing RV, by contrast, are neither individually nor jointly significant. Regression models 11-13 explore interactions involving EDUL, R&D and URBAN, and find no indications that such effects are at play (cf. tests for joint coefficient significance). Accordingly, we conclude that Model 10 (curvilinear effects but no interactions) best fit the data and proceed to compute marginal effects based on this specification.

Table 5: Baseline regression results, product innovation new to the world market.

	Dependent variable: RADICAL					
	Model 8	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**
	Coeff	*Coeff*	*Coeff*	*Coeff*	*Coeff*	*Coeff*
	(se)	*(se)*	*(se)*	*(se)*	*(se)*	*(se)*
AGE (log)	0.017	0.015	0.010	0.014	0.019	0.016
	(0.090)	(0.090)	(0.090)	(0.091)	(0.091)	(0.091)
SIZE (log)	0.088*	0.100**	0.084	0.086*	0.078	0.081
	(0.049)	(0.050)	(0.051)	(0.052)	(0.052)	(0.052)
R&D	1.314***	1.314***	1.312***	1.307***	1.174***	1.318***
	(0.128)	(0.128)	(0.129)	(0.129)	(0.173)	(0.130)
FORMAR	0.511***	0.512***	0.524***	0.526***	0.526***	0.529***
	(0.116)	(0.117)	(0.117)	(0.118)	(0.118)	(0.118)
EDUL	0.188**	0.180**	0.183**	0.229**	0.191**	0.182**
	(0.079)	(0.080)	(0.080)	(0.101)	(0.081)	(0.080)
CHURN	-0.661	-0.758	-0.970*	-1.015*	-0.990*	-0.920*
	(0.503)	(0.508)	(0.522)	(0.535)	(0.527)	(0.527)
URBAN	0.106	0.108	0.110	0.105	0.121	0.122
	(0.116)	(0.116)	(0.116)	(0.117)	(0.117)	(0.148)
TV	0.063					
	(0.057)					
RV		-0.065	-0.021	-0.355	-0.051	0.042
		(0.062)	(0.102)	(0.453)	(0.182)	(0.119)
RV^2			-0.017	0.257	0.016	-0.020
			(0.036)	(0.182)	(0.061)	(0.038)
URV		0.104*	0.179**	0.372	0.344*	0.205**
		(0.061)	(0.079)	(0.348)	(0.182)	(0.094)
URV^2			-0.071*	-0.134	-0.334**	-0.083*
			(0.037)	(0.185)	(0.154)	(0.045)
EDUL*RV				0.090		
				(0.115)		
EDUL*RV^2				-0.074		
				(0.049)		
EDUL*URV				-0.050		
				(0.088)		
EDUL*URV^2				0.017		
				(0.043)		
R&D*RV					0.050	
					(0.212)	
R&D*RV^2					-0.043	
					(0.073)	
R&D*URV					-0.208	
					(0.197)	
R&D*URV^2					0.292*	
					(0.158)	
URBAN*RV						-0.143
						(0.203)
URBAN*RV^2						-0.016
						(0.089)
URBAN*URV						-0.088
						(0.152)
URBAN*URV^2						0.033
						(0.077)
Constant	-3.493***	-3.447***	-3.253***	-3.429***	-3.170***	-3.264***
	(0.469)	(0.471)	(0.483)	(0.546)	(0.495)	(0.485)
Wald Chi2 tests of joint coefficient significance						
All terms involving RV			1.06	3.26	1.14	2.46
All terms involving URV			5.74*	5.93	7.65	5.98
Observations	1418	1418	1418	1418	1418	1418
LR Chi2 (df)	401.00(27)	403.01(28)	407.50(30)	410.07(34	412.30(34)	410.22(34)
R2	0.3381	0.3398	0.3436	0.3458	0.3477	0.3459

Note: Probit regressions. ***, ** and * indicate significance at the 1 per cent, 5 per cent and 10 per cent levels respectively.
All models are significant at p < 0.01

Fully in line with the baseline results, Table 6 demonstrate that the predicted probability of RADICAL does not respond to RV when all other variables including URV are held constant at the full sample mean. By contrast, when RV is held constant, increases in URV from low to moderate levels (up to 0.2 standard deviations above the mean) give rise to significant increases in the probability of RADICAL. In the range where marginal effect estimates are significant, the predicted probability triples. Yet, this 'at best' increase of 5 percentage-points in absolute terms before the effect of URV first flattens out and then turn insignificantly negative is moderate compared to a 15 percentage-point 'on average' increase in the probability of radical innovation that is associated with R&D activity[5].

Table 6: Predicted probabilities (PP) and marginal effects (ME) of diversity on RADICAL. Computed from Model 10 (N = 1418). 0 = mean diversity observed in the full sample.

RV	**PP**	**ME**	**SE**
-0.8	0.068	0.001	0.020
-0.6	0.068	0.000	0.018
-0.4	0.068	-0.001	0.017
-0.2	0.068	-0.002	0.015
0 (mean)	0.068	-0.003	0.013
0.2	0.067	-0.004	0.012
0.4	0.066	-0.004	0.010
0.6	0.065	-0.005	0.009
0.8	0.064	-0.006	0.008
1.0	0.063	-0.007	0.007
1.2	0.061	-0.008	0.007
1.4	0.060	-0.008	0.007
1.6	0.058	-0.009	0.008
1.8	0.056	-0.009	0.009
2.0	0.054	-0.010	0.009
URV	**PP**	**ME**	**SE**
-1.6	0.025	0.024	0.005***
-1.4	0.030	0.025	0.006***
-1.2	0.035	0.027	0.007***
-1	0.040	0.028	0.009***
-0.8	0.046	0.028	0.010***
-0.6	0.052	0.028	0.010***
-0.4	0.057	0.027	0.011**
-0.2	0.062	0.025	0.011**
0 (mean)	0.067	0.023	0.011**
0.2	0.072	0.021	0.010**
0.4	0.075	0.017	0.010*
0.6	0.079	0.014	0.010
0.8	0.081	0.010	0.010
1	0.082	0.006	0.011
1.2	0.083	0.001	0.012
1.4	0.083	-0.003	0.013
1.6	0.082	-0.007	0.014
1.8	0.080	-0.011	0.015

Note: Predicted probabilities and marginal effects of diversity computed at the mean effect of all other variables.

[5] See footnote 3.

4. Multicollinearity and robustness

In the base Models 1 and 8, the average variance inflation factor (VIF) is 1.19 and the maximum is 1.38. While the latter is well below the ‘rule-of-thumb’ level of 10 that indicate serious concerns (cf. Salmerón, García, and García 2018) a condition number (CN) of 24.90 indicate some multicollinearity as it is above the ‘rule-of-thumb’ level of 15. Still, it is below the level of 30 that indicate serious concerns (ibid; Belsley 1991). In Model 7 that describe the relationship between variety and incremental innovation, the average and maximum VIF is 2.3 and 3.73 respectively, and CN is 27.11. In Model 10 (best fit for RADICAL), the mean and max VIF is 1.50 and 2.8 respectively and CN is 25.24. All in all, this suggests that some multicollinearity is present as would be expected given the inclusion of polynomial terms for variables that are also moderately correlated with each other (RV/URV) and control variables (SIZE), but not a major concern (cf. bivariate correlations reported in Table A2).

To preserve observations, the analysis included multi-establishment enterprises that operate several plants in several locations. Following Herstad (2018b), these were assigned to the labour market regions in which they have the majority of their employment. This is not a trivial decision, as recent research suggest that the relationship between internal variety, location and performance is different in such enterprises compared to those that operate a single plant (Östbring, Eriksson, and Lindgren 2018, Herstad and Ebersberger 2014). To consider whether the choice to include such enterprises and the relocation procedure itself might substantively have influenced the results, supplementary estimations i) without the relocation procedure and ii) including only single-plant enterprises have been conducted. Besides reduced levels of significance due to lower numbers of observations, the results obtained were structurally consistent with those reported and discussed herein.

5. Discussion and conclusion

In this paper, we addressed the elementary yet open question of whether the novelty content of innovation reflect the composition of work-life experiences collected by employees prior to being combined in firms. To describe composition, we distinguished between variety of experiences from within (RV) versus between (URV) different industry groups. We took great care to isolate influences on innovation associated with worker experiences from those associated with their education levels, the R&D efforts of firms and their location. Finally, we acknowledged that these are also factors that might moderate the relationships of interest.

Neither incremental nor radical innovation respond to experience variety *per se*. Thus, no support is provided for Hypothesis 1a and 1b, and the importance of making the distinction between RV and URV is underscored by estimations finding conditional support first for Hypothesis 2a: Incremental innovation is strongly associated with RV. However, as this holds only when firms are located, and thus recruit, in a large-city region, Hypothesis H5 on interaction effects involving location is also supported. With respect to the latter, our empirical focus here on the basic urban-rural dividing line does not exclude that similar or even stronger effects are associated with location in other types of regions (e.g. industrial clusters) where labour markets facilitate sharing of experience-based knowledge between different-yet-related industries.

Further underscoring the receptiveness of INCREMENTAL to collected work-life experiences is the significant relationship with URV at low to moderate levels when firms do not engage in R&D. While it goes against the baseline assumption that URV is supportive foremost of radical innovation, it is supportive of Hypothesis H4 on R&D interaction and in line with the cognitive resource diversity theory in that *some* URV brings in new perspectives that are important in the absence of more systematic organizational learning efforts. At the same time, the insignificance of high URV suggests that there are limitations to the amount and degree of diversity that firms can effectively exploit, as suggested by the similarity attraction paradigm.

We did find support for Hypothesis 2b that predicted a positive relationship between URV and radical innovation. Yet, the relationship is also in this case significant only from low to moderate levels, before it first flattens out and then turns negative albeit insignificant at the highest levels considered. Furthermore, to accumulate URV, firms depend on employment turnover that in itself *reduces* the probability of radical innovation. Finally, the average impact of R&D on RADICAL by far outweighs the maximum impact from URV, and the effect of human capital described instead by education is not only strong but also independent of experiences.

In light of the specific empirical context here, these results suggest that modern manufacturing firms have a limited capacity to assimilate diverse cognitions, and transform such into radical innovation. More generally, they demonstrate that incremental and radical innovation depend on different resources and organizational processes, which translate into differences in receptiveness to the external environment: Whereas incremental innovation might be fuelled by movements of specialised skills between 'different-yet-related' industries in territorial contexts that facilitate such mobility flows, here approximated as URBAN, radical innovation depend on systematic corporate efforts in organizations with a stable and well-educated work-force that is enriched with *some* URV, but not too much of it. As such innovations are particularly important for internationally oriented manufacturing industries, individual job-hopping and corporate hire-and-fire strategies are problematic (Zhou, Dekker, and Kleinknecht 2011, Kleinknecht, van Schaik, and Zhou 2014) and governments should take care to not focus excessively on flexible labour markets as channels for knowledge diffusion. Instead, initiatives promoting intramural R&D efforts and the construction of innovation systems allowing firms and research institutions to cross-fertilize each other by other means (e.g. Coenen et al. 2016, Asheim, Smith, and Oughton 2011) while maintaining stable work-forces remain of high importance – at least in the manufacturing economy here considered.

This argumentation more than hints at a first limitation to our study. Due to extensive missing information, we were not able to investigate empirically whether the novelty content of innovation in services firms reflect the composition of work-life experiences collected by employees. This is a major limitation, as structural change favours services that might concentrate in large-city regions to benefit from learning through external labour pools (Herstad and Ebersberger 2014, Jøranli and Herstad 2017, Power and Lundmark 2004). In extension, we have left open also the more fundamental question of inter-industry differences in the receptiveness of innovation to labour replacement and the composition of experiences (cf. Herstad 2018a). Second, future studies should move beyond focusing on the binary location characteristic 'urban' that neither capture regional differentiation within nor outside the urban hierarchy. Instead, they should consider how the work-life experiences collected by employees are shaped by the actual variety, related and unrelated, of industrial activity in different regions (Frenken, Oort, and Verburg 2007, Aarstad, Kvitastein, and Jakobsen 2016), and interact with these region characteristics in influencing innovation in their employer firms (e.g. Aarstad and Kvitastein 2019).

Third, the survey data on innovation is cross-sectional. As innovation tend to persist over time (Cefis and Orsenigo 2001), the question of whether endogeneity is present because innovative firms also attract employees with certain career profiles is left open even through a lag was introduced between observed experience variety and observed innovation outcome. Another limitation given by the data used is that the linked employer-employee registers only allowed us to take a snapshot of the most recent work-life experiences collected by employees. While (relatively) recent experiences might well matter more for (some types of) innovation than past ones, the question does arise of whether the relationships here detected are more or less pronounced if longer career biographies, and thus higher overall levels of variety, are considered. Consequently, future studies should aim to construct diversity matrixes that extend beyond those used here, and explore also the temporal dimension that is the rate at which knowledge acquired in the past is ‘unlearnt’ as new, and potentially different, work life experiences are gained (cf. Lundvall and Johnson 1994).

Finally, our use of Norwegian data inevitably raises the question of whether results are influenced by specific economy characteristics that include specialisation in manufacturing and services industries that are closely related to natural resources and characterized by dense interactions with each other, and national champion research institutions (Herstad and Sandven 2017). It has traditionally been argued the Norwegian ‘variety of capitalism’, where strong unions negotiate with centralized business associations over working conditions and wages in manufacturing industries, is more supportive of collective learning processes within the boundaries of firms than external learning through labour markets (Asheim and Herstad 2005, Bosch 1997). These limitations simply underscore the need for future studies using data from other countries to take seriously the multi-dimensional nature of human cognitions and investigate in more detail how innovative capabilities are shaped by interactions between the strategies of firms, their accumulated human resources, and the labour markets of different locations.

Appendix

Table A1: Description of sample. Note: Actual (not standardized) RV and URV.

	Sample characteristics			Diversity				Innovation			
SN2007 2-digit	Description	Share of sample	URBAN	Mean RV		Mean URV		INCREMENTAL		RADICAL	
				URBAN =1	URBAN = 0	URBAN =1	URBAN = 0	URBAN =1	URBAN = 0	URBAN =1	URBAN = 0
10	Food products	0.15	0.38	0.158	0.156	0.591	0.648	0.24	0.18	0.06	0.05
11	Beverages	0.01	0.47	0.136	0.100	0.577	0.825	0.13	0.11	0.00	0.00
13	Textiles	0.03	0.28	0.063	0.090	0.511	0.777	0.00	0.10	0.08	0.19
14	Clothing	0.01	0.41	0.105	0.155	0.629	0.806	0.11	0.08	0.33	0.08
15	Leather	0.003	-	-	-	-	-	-	-	-	-
16	Timber & wood	0.07	0.20	0.046	0.081	0.425	0.634	0.13	0.18	0.00	0.01
17	Pulp & Paper	0.02	0.31	0.078	0.067	0.717	0.466	0.00	0.08	0.00	0.13
18	Printing & reproduction	0.03	0.58	0.123	0.124	0.438	0.651	0.18	0.15	0.00	0.00
20	Chemicals	0.04	0.32	0.076	0.153	0.757	0.910	0.15	0.14	0.15	0.21
21	Pharma	0.01	0.71	0.150	0.150	0.485	0.813	0.00	0.00	0.20	0.25
22	Rubber & plastics	0.04	0.29	0.074	0.087	0.662	0.814	0.19	0.13	0.00	0.21
23	Non-metallic minerals	0.05	0.27	0.092	0.062	0.707	0.829	0.29	0.20	0.05	0.05
24	Metals	0.03	0.15	0.052	0.079	0.637	0.761	0.00	0.13	0.14	0.05
25	Metal goods	0.11	0.36	0.109	0.126	0.637	0.815	0.08	0.06	0.08	0.11
26	Electronics & computers	0.05	0.63	0.100	0.163	0.877	0.950	0.13	0.03	0.50	0.52
27	Electrical equipment	0.04	0.37	0.102	0.065	0.999	0.804	0.20	0.21	0.36	0.17
28	Machinery & equipment	0.08	0.32	0.127	0.129	0.961	0.972	0.19	0.16	0.29	0.30
29	Automotive	0.03	0.30	0.044	0.047	0.573	0.731	0.08	0.03	0.15	0.23
30	Other transportation equip.	0.06	0.35	0.137	0.144	0.897	0.947	0.09	0.08	0.15	0.13
31	Furniture	0.04	0.16	0.030	0.097	0.346	0.584	0.33	0.21	0.22	0.17
32	Manufacturing n.e.c	0.03	0.51	0.039	0.019	0.553	0.479	0.00	0.11	0.10	0.16
33	Installation & repair of machinery	0.06	0.36	0.083	0.089	0.697	0.896	0.03	0.10	0.06	0.07
	Total (N=1463)	0.992	0.35								

Note: Data disclosure rules prohibit reporting of statistics for sector 15 Leather due to the low number of observations

Table A2: Descriptive statistics and correlations. N=1463 (all observations included in estimations of INCREMENTAL).

		Mean	**SD**	**Min**	**Max**	1	2	3	4	5	6	7	8	9	10	11
1	INCREMENTAL	0.137	0.344	0	1	1										
2	RADICAL	0.141	0.348	0	1	-0.161	1									
3	AGE (log)	2.912	0.579	1.609	4.718	-0.025	-0.011	1								
4	SIZE (log)	3.839	1.083	2.303	8.757	0.033	0.149	0.077	1							
5	R&D	0.396	0.489	0	1	0.262	0.421	0.004	0.282	1						
6	FORMAR	0.237	0.425	0	1	-0.115	0.322	-0.015	0.227	0.317	1					
7	EDUL	3.645	0.714	1	7.125	-0.003	0.320	-0.064	0.136	0.352	0.336	1				
8	CHURN	0.209	0.118	0	0.875	0.038	-0.112	-0.015	-0.049	-0.120	-0.112	-0.144	1			
9	URBAN	0.317	0.466	0	1	0.013	0.041	0.007	-0.027	-0.011	-0.041	0.187	0.032	1		
10	TV (std)	0	1	-1.928	4.465	0.022	0.145	-0.200	0.209	0.168	0.107	0.279	0.163	0.047	1	
11	RV (std)	0	1	-0.876	8.073	0.089	0.041	-0.144	0.210	0.089	0.079	0.125	0.066	0.050	0.587	1
12	URV (std)	0	1	-1.944	4.120	-0.003	0.154	-0.185	0.173	0.165	0.099	0.282	0.167	0.037	0.965	0.353

Computation of experience variety

We consider experiences collected in the years 2004-2008, meaning that each worker represent five experience-years. Each experience-year has been assigned a five-digit SN2007 industry code that capture the sector in which it was generated. If each firm has n types of experience-years present, represented by the industry classes and Pi is each 2-digit category's proportion of the total number of experience-years present within the firm, then the total entropy for each firm is given by Jacquemin & Berry (1979:360) as:

$$E_T = \sum_{i=1}^{n} P_i \ln \frac{1}{P_i}$$

Industry classes are structured hierarchically as specialized sub-fields within main aggregate fields. If we have s main fields, and Ps is the proportion of experience-years accounted in each, then the distribution of experience-years across main sector classes is given by Jacquemin & Berry (1979:361) as:

$$E_A = \sum_{s=1}^{s} P_s \ln \frac{1}{P_s}$$

Entropy within *each* sector class that is likewise given as:

$$E_w = \sum_{i \in s} \frac{P_i}{P_s} \ln \frac{P_s}{P_i}$$

The total entropy E_T may be expressed in the following way (see Jacquemin and Berry, 1979:362 for details):

$$E_T = \sum_{i=1}^{n} P_i \ln \frac{1}{P_i} = \sum_{s=1}^{s} P_s \left(\sum_{i \in s} \frac{P_i}{P_s} \ln \frac{P_s}{P_i} \right) + \left(\sum_{s=1}^{s} P_s \ln \frac{1}{P_s} \right)$$

Or simply:

$$E_t = \sum_{s=1}^{s} P_s \,(E_w) + E_A$$

Total entropy E_T is the total experience-variety of the firm referred to as TV. E_A is the entropy of the distribution across main industry classes referred to as URV. It follows that the sum of E_w weighted by P_s is also the difference between TV and URV that is referred to as RV.

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