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When are recruited competences supportive of innovation? Inter-industry differences in the importance of similarity and diversity

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Abstract

Building on recent evolutionary thinking, this paper links the present innovation performance of Norwegian firms to their past aggregate inflows of experienced employees through the labor market. In the upper part of OECDs technology intensity classification, firms strengthen their capacity to generate novelty sales by recruiting from within their own sector domains. By contrast, this form of recruitment is negatively associated with performance in low-tech industries. Aggregate inflows from related industries is generally supportive of performance, while inflows from prior employment in the research system is not. This underscores the dependence of industrial innovation on specialized competences and work practices that originate in the domain of industry itself; and, thus, the interdependencies between firms and larger industrial agglomerations.

Keywords: Labor mobility, related variety, knowledge integration, innovation, Norway

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Introduction

There is a strong and growing research interest in how the competences and labor market mobility of individuals mirror the characteristics of territorial economies (Eriksson et al. 2008), and, under certain conditions, provide individual firms with privileged access to valuable knowledge conveyed by their new employees from prior places of employment (Balsvik 2011; Maliranta et al. 2009; Møen 2005; Pesola 2011). A number of prior studies have mapped the mobility of specific occupational groups, such as top executives (e.g. Rao and Drazin 2002), university researchers (e.g. Herrera et al. 2010), dedicated R&D personnel (Maliranta et al. 2009) and patent holders (Breschi and Lenzi 2010; Maliranta et al. 2009; Oettl and Agrawal 2008; Singh and Agrawal 2011). Changing productivity growth, patenting propensities and citation practices in the wake of their career paths indicate that knowledge is transferred and exploited by new employer firms (Agrawal et al. 2006; Almeida and Kogut 1999; Herrera et al. 2010; Tzabbar 2009).

This type of mobility, however, poorly represents the actual flows that surround industrial organizations, and the many impulses that firms receive from their new employees. Others have therefore focused on the relationship between aggregate labor inflows and productivity growth (Balsvik 2011; Møen 2005; Pesola 2011). Currently, scholars in the rapidly growing field of 'evolutionary economic geography' (cf. Boschma and Frenken 2011b) are paying particular attention to the cognitive and spatial conditions under which cross-fertilization between firms occurs as a result of movements in the labor market (Eriksson and Lindgren 2009; Eriksson 2011; Timmermans and Boschma 2014).

This research has provided compelling evidence that aggregate mobility inflows do influence the productivity of firms, yet only conditionally so; depending on the degree of ‘relatedness’ (Frenken et al. 2007) between dispatching and receiving industries (Boschma et al. 2009). While the link between productivity growth and innovation capacity is complex (Crepon et al. 1998), the relevance of this to the understanding of industrial development work has recently been demonstrated by Herstad et al. (2015). This study finds the technical *inventive* capacities of firms, signaled by their patenting propensities, to be strengthened by aggregate inflows from universities and other dedicated research institutions. Their capacity to develop and introduce commercial innovations, by contrast, are strengthened only by inflows from firms in related industries (Herstad et al. 2015).

This recent extension of the industry relatedness framework to focus on inventive and innovative output align with the original framework in leaving the essential question of inter-industry differences in the link between aggregate inflows and performance open. The economy-level parallel to this is the issue of how and when the build-up of innovation capacity is supported by localization economies, attributable to industrial specialization and strong industry-specific pools of experience-based knowledge available for firms to tap (cf. Marshall 1920), or urbanization economies, attributable to local industrial diversity and breadth of knowledge supply (Beaudry and Schiffauerova 2009; Glaeser et al. 1992; Jacobs 1969). Following recent calls for such studies (Timmermans and Boschma 2014), this paper analyzes whether the commercial innovation performances of firms in high-tech industries and in low-tech industries are influenced differently by the different categories of labor inflow that are captured by the extended industry relatedness framework of evolutionary economic geography (cf. Herstad et al. 2015).

Empirically, the analysis is based on register data covering all Norwegian enterprises and citizens of age 16 or above in annual waves from 2001 to 2006. These have been merged with official survey data on innovation activities and outcomes during the following period 2006-2008 (Community Innovation Survey data (CIS), cf. OECD 2005). Linked employer-employee (LEED) registers are maintained by governmental authorities, while the CIS data used were gathered in accordance with EUROSTAT guidelines by Statistics Norway in 2008. This combined CIS-LEED dataset allows innovation performance observed in 2008 to be regressed on a set of recruitment intensity indicators that refer to the period 2001-2006, and controls for other important aspects of firms' innovation activities during the period 2006-2008 to be implemented. To set the stage for this, we first describe some notable characteristics of the Norwegian economy and the development trends that has characterized it during the last decade.

The Norwegian industrial and institutional context

Norway is a small, open and high-income economy. The industrial system is strongly specialized in deep-water oil and gas extraction technologies, seafood, maritime equipment, ammunition and weapons systems, and metallurgical industries (e.g. Benito et al. 2002; Fagerberg et al. 2009). These are largely engineering-based; characterized by cumulative knowledge development and continuous innovation aimed at problem solving in specific contexts of technology application. A unique feature of the Norwegian research system is the applied research institute sector that has evolved in dense interaction with incumbent industries (cf. Narula 2002) and grown to be become very large by international standards.

Work within the varieties of capitalism tradition has suggested that competitive advantages in these types of industries are dependent on systems of industrial relations that ensure stable funding, long-term strategies and commitment of individual employees to firm-specific and sector-specific knowledge development (cf. Bassanini and Ernst 2002; Estevez-Abe et al. 2001; Herstad 2011; Kleinknecht et al. 2014). While direct legislative constraints on mobility in the Norwegian labor market are, by continental European standards, weak (Knell and Srholec 2006); strong unions and industry associations have negotiated extensive employee co-determining rights in corporate decision making (Dølvik et al. 1997). Combined with extensive state ownership in publicly listed incumbent firms, this has formed the institutional basis for private sector strategies favoring training and reallocation of staff rather than adjustments through the external labor market (Herstad 2005; Thomsen 1996). Furthermore, collective wage bargaining has resulted in a compressed wage structure with relatively low salaries in the upper end of the skill spectrum (Hunnes et al. 2009; Hægeland et al. 1999; Iversen and Soskice 2010), and has dampened, but far from eliminated, inter-firm mobility driven by wage differentials and 'poaching' of skilled employees (Combes and Duranton 2006).

Throughout the period in question, the Norwegian economy exhibited strong growth and high employment levels. Compared to other economies, it was only marginally influenced by the ICT bubble burst of the early 2000s and the advent of the financial crisis in late 2007 (Herstad 2011). This resilience has largely been due to strong demand for offshore oil and gas extraction technology in the wake of high international energy prices; to strong export markets for seafood; and to growth in the exports of weapons systems and ammunition (Castellacci and Fevolden 2014). Consequently, neither institutional conditions nor turbulence during the period for which the relationship between aggregate inflows and performance is estimated represents obvious sources of biases.

Industrial innovation performance

The capacity to continuously develop new products, introduce them onto the market and generate sales is a particularly important driver of growth (Coad and Rao 2008; Wiklund et al. 2009) and long-term, competitive advantages (Cohen and Klepper 1996; Ebersberger and Herstad 2011). Following Danneels (2002) and Grant (1996), this capacity depends on the creative linking of emerging technological opportunities and evolving market demand to organizational capabilities that extend well beyond those that can be contained and controlled by R&D departments or other single units within the firm (Danneels 2002; Hoopes and Postrel 1999; Zahra and Nielsen 2002). Therefore, product development projects are often 'organizationally complex' in that they depend on the effective mobilization and integration of different forms of knowledge and capabilities (Herstad et al. 2015). As such, they are particularly forceful drivers of broad-based organizational upgrading and renewal. Inventive capacity, by contrast, can be built and expressed in the form of patent output without the active contribution or organizational communities beyond R&D, or partners beyond research communities (Jensen et al. 2007). It can even be contained and controlled by a very limited number of 'superstar' scientists (Breschi and Lissoni 2001; Tzabbar 2009). Such concentration of resources and efforts translates into a higher capacity to deal with cutting-edge scientific knowledge and technological complexity (Herstad et al. 2015) in specific fields, yet, it is paralleled by a lower capacity to mobilize creativity on a broader basis (cf. Østergaard et al. 2011) and relate to the actual contexts of application of products and production processes (Jensen et al. 2007).

The strengths and intrinsic characteristics of innovative capacities evolve cumulatively. Over time and depending on the management attention received (Ocasio 1997), preferences for projects of a given type, size, and risk level become institutionalized within the firm as routines. These favor certain key resources, success factors, stages of product life cycle, or product-market positions (Lane and Lubatkin 1998). Because these routines, and the knowledge assets they express, reflect past problem-solving activities (Ahuja and Katila 2004), they are inherently specific to individual firms and heterogeneous between them (Birkinshaw et al. 2002; Pennings and Wezel 2007; Wernerfelt 1984).

New employees enter into this with categories of cognition, i.e. of perception, sense-making, inference and enactment (Nooteboom et al. 2007), that reflect their educational backgrounds and prior work-life experiences. This means, first, that they provide their new employer firms with privileged access to specialized knowledge, experiences and insights gained at prior places of employment (Song et al. 2003). This knowledge is, second, expressed in ways which reflect work processes, organizational routines and codes for communication prevalent amongst their former employer organizations (Aime et al. 2010; Dokko et al. 2009; Madsen et al. 2003; Wezel et al. 2006).

Individuals are also embedded in interpersonal networks that reflect the geographical and cognitive domains covered by their career paths (Agrawal et al. 2006; Corredoira and Rosenkopf 2010; Oettl and Agrawal 2008). It is well established that these networks may continue to convey valuable information between past and present places of employment long after the mobility event itself (Bouty 2000; Dahl and Pedersen 2004). As a result of this, new employees may, third, broaden the firm's search for new technology and market opportunities, reorient the search process in the direction of specific cognitive domains or reinforce the emphasis put on searching domains already known (Laursen 2012; Laursen and Salter 2006; Rosenkopf and Almeida 2003).

In order to influence organizational dynamics, the resources that new employees embody must not only represent potential novelty value. They must also be communicated in a manner that allow new thinking to be triggered, and be similar enough for this novelty value to materialize through integration into the pre-existing knowledge bases and routines of the recruiting organizations (Cohen and Levinthal 1990; Grant 1996). At the level of individuals, this can be captured in terms of the degree of cognitive distance (Nooteboom 2000; Wuyts et al. 2005) involved at the intersection between new employees and the people, work practices and routines that most immediately provide the link to the larger organizational system that surrounds them at their workplace (Singh and Agrawal 2011; Tzabbar 2009).

When individuals share similar experience-based backgrounds, they communicate easily and align preferences in a manner that is more likely to reinforce established practices than to trigger new thinking. When the experience-based competences of recruits are very different from those they encounter in their new positions, they may challenge established practices, trigger improvements in work processes and allow the firm to identify new opportunities. However, new employees may also experience problems in achieving status as legitimate ‘insiders’ to established organizational communities (Lave and Wenger 1991; Wenger 1998), and their insights may even be deemed irrelevant. In fact, the entry of cognitions very dissimilar to those that already dominate within the firm may translate into tensions that cause the firm to retain rather than adjust established practices (Dokko et al. 2009; Katz and Allen 1982; Madsen et al. 2003; Østergaard et al. 2011).

The cognitive distances involved in aggregate mobility flows have previously been captured in terms of the degree of relatedness between the industries wherein experiences have been gained, and the industries into which they enter (Boschma et al. 2009; Eriksson and Lindgren 2009; Eriksson 2011; Frenken et al. 2007). Herstad et al (2015) extent this framework into the realm of innovation, and show that the intensity and consistency of different types of inflows may influence not only the strength of recruiting firms' capacities to innovate, but also the intrinsic characteristics of these capacities as expressed in terms of contrasting propensities to invent and patent, develop and introduce new products onto the market, and continuously improve production processes and support functions.

Still, the ability to generate sales and support market positions through innovation depends more on the actual characteristics of new products, than on new product introductions per se or the novelty of technologies that have been developed and applied. Moreover, it depends on a number of other factors such as understanding of the intersection between technological opportunities and market needs, complementary capabilities and parallel process innovations, external network configurations and the ability to predict, and effectively relate to, competitor responses (Danneels 2002; Danneels and Kleinschmidt 2001; Grant 1996). The question of how, and when, the exposure of firms to experience-based knowledge through aggregate mobility inflows is translated into support for commercial innovation performance thus requires dedicated research attention.

Hypotheses

Reflecting the work of Herrera et al (2010) and following closely Herstad et al. (2015), we first consider the special case of recruitment from the research system, i.e. from prior employment at universities, other higher education institutions and research institutes. This involves the transfer of cutting-edge scientific knowledge, provides contact points to global research communities and introduces habits and work practices that reflect the norms and incentive structures of academia. These norms include emphasis on the creation and dissemination of new 'global' technology and knowledge (Becher and Parry 2005; Jensen et al. 2007). Such inflows may force new thinking within the firm, support technological repositioning and provide an important part of the basis for the build-up of technical inventive capacity (Herrera et al. 2010; Jensen et al. 2007; Tzabbar 2009).

However, substantial efforts may be required in order for scientific knowledge and new technologies to be adapted to 'local' firm and customer needs, and thus eventually come to support commercial performance. These processes of adaption are firm-specific, and individuals with cognitions shaped by academic work practices and incentive structures may be difficult to integrate into them (Becher and Parry 2005; Dokko et al. 2009). While the entry of former research system employees may substantially strengthen the technical inventive capacity of firms and their propensity to introduce radical innovations onto the market, it is less obvious that they serve in support of commercial innovation performance. Strong and consistent inflows may even reduce the attention of the firm towards organizational processes that are essential to this performance, such as continuous, incremental improvements of product and production processes (Herstad et al. 2015). Our first Hypothesis acknowledges this:

H1: Past inflow of employees from prior employment in universities, research institutes or other higher education institutions (i.e. the 'research system') is not associated with present innovation performance

Still, from the literature on sectoral systems of innovation (Pavitt 1984), industrial knowledge bases (Herstad et al. 2014) and technological regimes (Breschi et al. 2000; Marsili and Verspagen 2002) it is known that firms differ in the extent to which their products and production processes depend on scientific knowledge and directly incorporate technological advances; and, consequently, whether they have developed knowledge bases and processing routines that reflect this (Herstad and Brekke 2012; Jensen et al. 2007). A second hypothesis can therefore be formulated to recognize that firms in industries that are particularly technology-intensive may be better positioned, in terms of their markets, and equipped, in terms of pre-existing knowledge bases and routines, to translate aggregate inflows of experiences from the research system into support for commercial innovation performance:

H2: In high technology intensity industries only, past inflow of employees from prior employment in the research system is positively associated with present innovation performance

Aggregate inflows from other firms in the same sector involves individuals who understand the rules of the game and can readily enter into prevalent ways of working (Boschma et al.

2009; Dokko et al. 2009; Madsen et al. 2003). This type of recruitment is likely to reinforce ties to sector-specific networks and deepen rather than broaden the knowledge base of the firm. In general, it is therefore not very likely to be supportive of innovation performance. In fact, such inflows may serve to confirm the soundness of established practices, in particular, when employees are mobile between industries wherein knowledge development is cumulative and path-dependent and technological change is incremental. This translates into a next set of hypotheses:

H3: Past inflow of employees from firms in the same industry is not associated with present innovation performance

H4: In low technology intensity industries only, past inflow of employees from firms in the same industry is negatively associated with present innovation performance

Intra-sectoral flows of experienced labor still provide individual firm with insights into industry trends and competitor responses to them. Consequently, it should increase the ability of the recruiting firm to stay abreast with markets and technological advances specific to the sector, and monitor competitor responses to own strategic moves. This can be assumed important to innovation performance in technology intensive industries specifically, due to rapid rates of more radical technological change, stronger pressures to transform new technology into products and the higher dependence of each individual firm on access to sector-specific information, knowledge and organizational practices that result from this:

H5: In high technology intensity industries only, past inflow of employees from firms in the same industry is positively associated with present innovation performance

When individuals move between different industrial sectors, they contribute to the diffusion of experience-based knowledge originating in commercial and technological settings different from those of their new employer organizations (Frenken et al. 2007). Distant resources may help firms to overcome path-dependencies by broadening innovation search, by diversifying otherwise highly specialized organizational knowledge bases and by challenging prevalent organizational practices and routines. However, inflow of employees with very different experience-based backgrounds exerts inconsistent influences. This can create tensions (Østergaard et al. 2011), to which the recruiting firm may respond by retaining rather than adjusting established practices (Madsen et al. 2003; Mintzberg 1993).

Herstad et al. (2015) find extensive inflows from unrelated industries to be negatively associated with improvements of production processes and support functions. Inflow from related industries, by contrast, is found to provide unconditional support for product innovation, and to serve as a catalyst for parallel process innovations. Inflows from related industries can therefore be expected to be supportive also of commercial innovation performance. Moreover, this support should be most pronounced in industries that are particularly dependent on continuous improvements of products, production processes and support functions, and thus on experience-based knowledge embedded in firm-specific organizational routines. It should be less pronounced in those industries that more directly depend on translating scientific advances and new technology into commercial products. From this follows a last set of hypothesis:

H6: Past inflow of employees from firms in related industries is positively associated with present innovation performance

H7: In low technology industries, the positive association between past inflow from firms in related industries and present innovation performance is more pronounced than in high technology industries.

Empirical analysis

Data

The empirical analysis is based on Norwegian innovation micro-data, which cover innovation activities and outcomes in a representative sample of firms during the period 2006-2008. It was collected by Statistics Norway in 2008, as an extended version of the harmonized pan-European Community Innovation Surveys commonly abbreviated ‘CIS' (Eurostat 2010). The questionnaire is based on the definitions of innovation input (R&D and non-R&D expenditures), external linkages (technology sourcing and innovation collaboration) and output laid out in the second revised edition of OECD`s Oslo Manual (OECD 2005). Only firms with five employees or more in 2008 are surveyed. In contrast to many other European countries, participation was compulsory for sampled Norwegian firms. This resulted in a comparatively large data set, which is not plagued by a non-response bias. The data was thoroughly reviewed and validated by Statistics Norway prior to release for research purposes.

Information on recruitment during the years 2001-2006 has been generated from linked employer-employee registers available on an annual basis, and added to the CIS data using the anonymized identifiers supplied by Statistics Norway. Linked employer-employee (LEED) registers are maintained by governmental agencies. They are available for research purposes as annual sets that includes all Norwegian citizens above age 16, and all individuals employed in Norway irrespective of citizenship. This type of data has been used in a number of closely related studies (Balsvik 2011; Boschma et al. 2009; Herstad et al. 2013; Maliranta et al. 2009). CIS has similarly been used extensively for analysis in economics, economic geography and management studies (e.g. Cassiman and Veugelers 2006; Ebersberger and

Herstad 2012; Grimpe and Kaiser 2010; Herstad and Ebersberger 2013; Laursen and Salter 2006).

The analysis uses 3,197 observations from manufacturing, knowledge intensive business services, aquaculture and extraction of petroleum and natural gas. As inflow can be expected to influence new and established firms in different ways (e.g. Agarwal et al. 2004), only receiving firms established at least five years prior to the 2008 innovation survey sampling and active in the labor market at least one year prior to the start of the reference period in 2006 are included this sample. No restrictions are implemented on dispatching firms or institutions. Key sample characteristics are described in Table 1.

Selection and dependent variables

The selection variable ACTIVE captures the decision to engage in systematic development work. It follows the routing structure of the CIS questionnaire and takes on the value 1 if the firm reported positive innovation expenditures (R&D or non-R&D), finalized, ongoing or abandoned innovation projects, or positive innovation outcomes during the period 2006-2008 (e.g. Ebersberger and Herstad 2012).

Several alternative measures for innovation output based on information available in CIS have been applied in the literature, and span from technological inventions signaled by patent applications to various measures constructed from the information provided on new product launches and process implementations. Among these, innovation sales provide the best single empirical indicator of innovation performance as defined and discussed in substantial terms above. In the analysis herein, performance is therefore captured as the share of total turnover in 2008 generated by new or significantly improved goods or services introduced during the prior 2006-2008 period. The dependent variable TURNIN has been extensively used in prior research (cf. Ebersberger et al. 2012; Herstad et al. 2008; Spithoven et al. 2012). Averages per sector are described in Table 1 below.

Independent variables

Inflow intensity indicators are constructed by first computing the total number of inflow events during the period 2001 throughout 2005, i.e. to the start of the CIS reference period. Each inflow event is discounted by an annual rate of 15 percent (e.g. Czarnitzki 2005; Griliches and Mairesse 1984; Hall 2007; Hall et al. 2010) from the base year of 2006, and the sum of discounted events is normalized by the size of the target firm this year. In a limited number of cases, a combination of small size and large aggregate inflows causes this procedure to produce extreme values. Therefore, the maximum values used in the regressions are set equal to the cut-point values for the 99th percentiles of each initial inflow intensity distribution. Educational levels are used as a proxy for the ability of individuals to embody and convey cognitive resources (Lorenz and Lundvall 2010; Nelson and Phelps 1966), and the prior sector of employment to proxy the characteristics of these resources (Boschma et al. 2009). Only individuals that are in LEED assigned an educational code equivalent to a bachelor degree or above and entered the focal firm directly from prior employment are included in the main inflow intensity indicators.

When receiving and dispatching firms are assigned to different main (NACE two-digit) industry classes, they are assumed to represent fundamentally different cognitive domains and inflow is captured by the intensity indicator UNRELATED. When dispatching firm operate in the same five-digit NACE group as the firm that is recruiting, they operate in the same industry and inflow is captured by the intensity indicator SAME. Last, when mobility occurs between firms that are classified in the same main (NACE two-digit) sector but in different subgroups (NACE five-digit), they are assumed to represent different yet related industries and the corresponding inflow intensity indicator is denoted RELATED.

These classifications of aggregate inflow from industrial sources are in accordance with the original industry relatedness framework of evolutionary economic geography (Boschma et al. 2009; Boschma and Frenken 2011a; Eriksson 2011; Frenken et al. 2007), as applied also in Herstad et al (2015). Following the latter, the framework is extended to include the variable RESEARCH in order to capture specifically the intensity of past recruitment from prior employment in the research system, i.e. aggregate inflows from prior employment at universities and university colleges, and in private or public research institutes. The use of one single variable to capture this type of recruitment has precedence also in Herrera et al. (2010).

Sector controls and technology intensity classes

The NACE industry codes provided in the CIS[2] have been used to classify manufacturing firms into 16 sector groups. Knowledge intensive business services have similarly been classified as either ‘new technology based’ or as ‘traditional professional services’ (cf. Miles 2008; Shearmur 2012) . Last, aquaculture and petroleum extraction industries are idiosyncratic to the Norwegian economy and classified as such.

This gives 20 industry groups in total, which are represented by 19 industry dummies in the regressions. These are described in Table 1. The descriptive statistics provided in this table shows that recruitment from the research system is particularly pronounced in high-tech manufacturing and in knowledge-intensive business services (KIBS). KIBS also align with

[2] ‘The Norwegian SN2002 industry standard is used. This correspond to ISIC revision 4.

firms in the electronics sector in exhibiting above-average intensities for recruitment within own sector. The importance of controlling for sectors is further underscored by the differences in average innovation performance between the different sector groups.

Firms belonging to the six industry groups that are either defined by the OECD as medium high-tech manufacturing or high-tech manufacturing, or characterized by the literature as 'new technology based services' (T-KIBS, cf. Miles 2008; Shearmur 2012), are additionally assigned the value 1 on the variable HIGHTECH that is used to construct the interaction terms needed to evaluate the predictions of Hypothesis H2, H4, H5 and H7. This means that 'traditional professional services' (P-KIBS) are defined as low-tech. The OECD classification of manufacturing industries is based on the direct R&D intensity of sectors as well as their dependence on technology embodied in intermediate and investment goods (Ejermo et al. 2011; Hatzichronoglou 1997). While this must not be confused with knowledge intensity or complexity of output (Herstad et al. 2014), it provides us with the approximation for the direct dependence of firms on scientific knowledge production that is needed to reflect the underlying assumptions of these hypotheses.

Table 1 approximately here

Other control variables

Innovation performance can be expected influenced by the emphasis put by the firm on the development of new products, irrespective of past recruitment and the overall demands imposed by the sectors to which firms belong. To control for this effect, the binary variable

PRODUCT is included that takes on the value 1 if either one of the three product innovation objectives specified in the questionnaire (diversification of product portfolios, replacement of outdated products, improvement of product quality) are rated as more important motivations for development work than any other of the remaining nine that capture process innovation objectives and environmental impact objectives. Innovation performance is influenced by established market positions, search spaces, knowledge bases and routines, and these may be linked to the size and age of the firm (Rao and Drazin 2002). The logs of firm age and firm size are therefore included as controls. Furthermore, MARBREADTH captures the proportion of world regions specified in the CIS questionnaire on which the firm indicates a market presence[3].

Two variables are included to isolate the effects of the inflow intensities of interest from effects attributable to the growth trajectory and overall exposure of the firm to new employees (Audretsch 1995; Herstad et al. 2013; Wiklund et al. 2009). The control variable RESIDUAL capture accumulated residual recruitment from 2001 and throughout 2005, i.e. all recruitment events, irrespective of education levels and prior places of employment, that are not captured by the main intensity indicators. It is depreciated and normalized by the size of the firm in 2006 according to the procedure described above. The variable GROWTH is computed as the sum of annual employment growth rates for the years in existence after 2001, averaged over the number of years.

Last, innovation outcomes are determined by the overall emphasis put by the firm on development work and the extent to which it strategically uses knowledge and technology

[3] The world regions in which market presences can be stated are: Norway, other Nordic Countries, other European Countries, North America, Asia and other

from different types of collaboration partners. Controls are therefore included for innovation expenditures per employee (INNOVINT); for the proportion of these expenditures used for arms-length sourcing of technology, expertise and R&D services (INNOVEX) and for the fraction of partners given in the CIS questionnaire stated as actively used by the focal firm (COBREADTH)[4]. The use of a breath measure to describe collaboration build on the approach of Laursen and Salter (2006) in accordance with Herstad et al. (2008) and subsequent empirical applications of their framework (Ebersberger et al. 2012; Spithoven et al. 2012). Descriptive statistics and bivariate correlations are reported in Table 1 below and in Table A3 in the Appendix.

Innovation intensity includes reported expenditures on intramural and extramural R&D, other (non-R&D) internal expenditures associated with knowledge development, and external expenditures associated with the acquisition of (non-R&D) expertise. The distinction between external expenditures and collaboration reflects the definition of collaboration applied in the CIS questionnaire, which explicitly asks respondents to include only partners actively involved in development work and exclude the pure contractual sourcing captured by INNOVEX. It is increasingly emphasized in the academic literature, because of the different implications of internal efforts, collaborative development work and contractual sourcing respectively for knowledge accumulation within the focal firm (Ebersberger and Herstad 2011; Fey and Birkinshaw 2005; Grimpe and Kaiser 2010; Kessler et al. 2000; Schmiedeberg 2008; Teirlinck et al. 2010; Weigelt 2009).

[4] The types of partners with whom collaboration can be stated are: Other units within parent enterprise group, clients, suppliers, competitors, consultancy firms, universities and other higher education institutions, commercial R&D laboratories, private and public R&D institutes.

Estimation strategy and sample selection issues

The main dependent variable is a fraction bound between 0 and 1. Conventional regression methods are therefore inappropriate (Greene 2000), and the fractional logit estimator (Papke and Wooldridge 1996) is applied (cf. Baum 2008; Ebersberger et al. 2012; Spithoven et al. 2012). The regressions are run in a base form and in a full form that include interactions terms between the technology-intensity dummy HIGHTECH and the inflow intensities. Detailed predicted probabilities and marginal effects are then computed and discussed.

The availability of information needed to estimate innovation performance is contingent on the decision to engage in development work (Herstad et al. 2015). This translates into a potential sample selection bias, because unobserved determinants of the decision to engage may also influence innovation performance (Cassiman and Veugelers 2006). The selection variable ACTIVE is binary and estimated by the probit regression (Model 1). When the Mills Ratio (MR) is estimated on the basis of this (Greene 2000; Heckman 1979) and included in the outcome stage (Model 2) as a control for sample selection, it is not significant and the results are not structurally altered. Due to this, and the absence of the instrumental variable that must be included to credibly establish that estimates are not biased by the selection procedure itself, controls for sample selection are not implemented (Bushway et al. 2007; Puhani 2000). The results of the selection stage is still reported as a backdrop for the outcome regressions that speak directly to the hypotheses.

Results

Baseline regression results

Table 2 reports the results of Model 1, in which the decision to engage in innovation activity is estimated. It is positively associated with size and the geographical breadth of market presence. Not surprisingly, it is also positively associated with recruitment from the research system and from unrelated domains. On the other hand, it is negatively associated with recruitment from within the same industry, and with residual inflow. The latter is consistent with recent research that has found the innovation activity decision of firms to be negatively influenced by high turnover of employees (Herstad and Ebersberger 2014). More generally, it is well aligned with the notion that stability in the human resource base increases the willingness of the firm to invest in development work (eg. Suarez-Villa and Walrod 1997; Zhou et al. 2011).

Overall, these results indicate that larger and diverse markets, and more diverse high-skill labor entering into the firm, positively influences the decision to engage. Conversely, a strong orientation towards familiar domains reinforces the focus of the firm on established products and practices to the extent that it may decide not to engage actively in development work. The negative coefficient estimate for age is supportive of this interpretation, because increasing age may be associated with the development and institutionalization of organizational rigidities which translate into cognitive lock-ins (Leonard-Barton 1992).

Table 2 approximately here

The baseline results for INNOVINT and COBREADTH in the regressions estimating TURNIN (Model 2A and 2B in Table 2) underscore the importance of commitment of financial and human resources to the build-up of internal knowledge bases, and of complementary partner resources. Consistent with prior research (Ebersberger and Herstad 2011; Kessler et al. 2000), this importance is further underscored by the negative estimate for INNOVEXT; the share of total innovation expenditures captured by INNOVINT that is allocated to technology sourcing or purchases of contractual R&D services. The positive estimate for average annual growth may indicate that internal competences and routines built during past growth processes are supportive of commercial performance at present (Audretsch 1995; Herstad et al. 2013; Wiklund et al. 2009); or, alternatively, that this performance is linked to market positions established as a result of past growth. Last, the absence of significant coefficient estimates for innovation strategies with a strong singular emphasis on product innovation (PRODUCT) underscores how the capacity to generate novelty sales is a multi-dimensional organizational capability that is linked to other aspects of the firm than its singular emphasis on new product development.

Model 2A find innovative sales to be positively associated only with the intensity of inflow from the same industrial sector (same NACE 2-digit) and from industrial sectors defined as related (same NACE 2-digit, different 5-digit). When two-way interactions with technology intensity class are included in Model 2B, the results suggests that benefits from intra-sectoral recruitment are exclusive to firms that operate in high-technology intensity sectors, whereas firms in low-technology intensity sectors are found to have benefitted from recruitment outside their own main (NACE 2-digit) sector groups. Aggregate inflows from related industries is found to be beneficial for performance in both technology intensity classes, whereas aggregate inflows from the research system recruitment are not, in either class.

Detailed marginal effects analysis

The size, and thus substantial interest, of the results are difficult to establish directly from logit coefficient estimates. It is therefore recommended that marginal effects are computed (Hoetker 2007). However, single marginal effect estimates computed under the required assumptions as to the values of other covariates (Bartus 2005; Greene 2000) are difficult to interpret when squared terms and interaction terms are involved (Ai and Norton 2003). This is because they may vary at different levels of inflow intensity, and differently so between subpopulations (cf. Ebersberger and Herstad 2011 for an elaborate example). To acknowledge this, we have standardized the regression coefficients of Model 2A and 2B, and, for each inflow intensity, predicted marginal effects and innovation performance in a range spanning from the approximate minimum value through the mean of 0 and up to 2.75 standard deviations above the mean[5]. Holding all other variables constant at their respective means, the results are first estimated for all firms without the inclusion of interaction effects (based Model 2A reported in Table 2). Performance and marginal effects are then computed with interaction effects included. This is done separately for the two technology intensity classes (based Models 2B reported in Table 2); and, thus, with other variables held constant at the respective subpopulation means. The significance of the marginal effects, i.e. whether the gradients of the curves are statistically different from zero, are indicated by full lines (significant at $p < 0.1$) or dotted lines ($p>=0.1$). The discussion is centered on the relationships

[5] For SAME, RELATED and RESEARCH, predicted performance is for the sake of graphical presentation estimated at minimum values of 0.5 SD below the mean. The actual minimum values for the three variables in the sample are -0.44/-0.42/-0.33 SDs respectively. The minimum value for UNRELATED in the prediction is 0.75 SD below the mean; whereas the actual minimum value in the sample is -0.8 SD. Between 2.74 per cent (UNRELATED) and 3.18 per cent (SAME and RESEARCH) of each distribution have scores higher than 2.75 standard deviations and are therefore not represented in the figures.

detected from the minimum through the mean and up to +1 SD. This range represents 91.03 per cent of the distribution for SAME; 89.6 per cent of RELATED; 87.51 per cent of UNRELATED and 92.63 per cent of RESEARCH.

Figure 1 approximately here

Figure 1 above describes the predicted relationship between performance and past intensity of research system recruitment, and shows no significant associations that are of substantial interest. This is consistent with Hypothesis H1, in which this pattern was postulated for the sample as a whole. Moreover, it can be noted that the only indication of an increase in predicted performance is detected for firms in low-tech industries, from 0.091 at the minimum to 0.102 at the inflection point, equal to a 12 per cent increase in the sales share.

Large standard errors of the marginal effect estimates for RESEARCH suggests that the absence of systematic support for performance may be due to inconsistent influences among the 207 innovation-active firms in low-tech industries (19.15 per cent of this subpopulation) that have recruited from the research system, and thus that it is a high-risk human resource strategy from which some firms do benefit when they are able to identify and recruit the right individual experts. However, this and the more clear-cut absence of significant estimates for the 223 firms in high-tech industries (30.26 per cent of this smaller subpopulation) that exhibit such recruitment is inconsistent with the notion that firms in these industries are systematically better positioned, in terms of market demand, and capable, in terms of organizational knowledge bases and routines, of translating aggregate inflows of experiences gained in the research system into performance. No support for Hypothesis H2 is therefore provided.

Figure 2 approximately here

Figure 2 shows that recruitment from within firms' own sectors does not influence performance in the sample as a whole to any degree that is of substantial interest. This consistent with Hypothesis H3, and reflect the findings of prior research (Herstad et al. 2015). However, it conceals highly notable differences between the technology intensity classes that translate into strong support for Hypothesis H5. In the high-tech group, this type of recruitment increases the predicted novelty sales from 0.209 at the minimum intensity to 0.266 before the marginal effect loses significance at 0.75 SD above the mean. This equals an estimated increase in novelty sales share of 27 per cent. Equally striking is how we find the novelty sales of firms in the low-tech group decreasing once the intensity has reached a level equal to 1 SD above the subsample mean. Still, the zero effect around the mean best represent the sample as a whole, and the support for Hypothesis H4 is therefore weak and conditional.

Figure 3 approximately here

The dependence of firms in low-tech industries on exposure to competences and work practices that challenge established products and practices, and thus originate outside the recruiting firms' own sector domains, is evident also from the marginal effects of unrelated inflow, described in Figure 3 above. While no significant marginal effects are detected in the sample as a whole, they are positive and significant for low-tech firms throughout the reported response surface. From -0.75 SD and up to the mean, the increase from 0.084 to 0.098 equals 16 per cent, while the predicted increase up to the reported maximum of 2.75 SD above the mean equals 79 percent.

Predicted performance as a function of RELATED is described in Figure 4 below. In the sample as a whole, the estimated increase in novelty sales through the range wherein marginal effects are significant equals a strong 26 per cent. Positive marginal effects are not significantly different from zero for high-tech firms as such; yet, as is evident from the HIGHTECH*RELATED estimate in Model 2B, they are neither significantly different from the positive effect detected in the low-tech sample. For these firms specifically, the increase in predicted novelty sales shares from 0.087 at zero inflow to 0.108 at 0.5 SD where the marginal effects loses significance equals a strong 24 per cent. Because this means that all firms increases their capacity to generate novelty sales by recruiting from related industries, it is supportive of Hypothesis H6 but contradictory to the predictions of Hypothesis H7.

Figure 4 approximately here

Robustness

Labor market movements involve processes of search and matching (Balsvik 2011). This means that i) the most competent employees may be attracted to the strongest performing firms, and that firms may ii) chose to hire certain types of employees at one point in time to build capacity in support of later development work. Thus, when inflow and output is temporally proximate, the directions of causality is difficult to determine and estimates are at risk of being upward-biased by endogeneity. Furthermore, some types of knowledge may require more time in order to be reflected in new products and translate into performance (Breschi and Lissoni 2001). As a robustness test reflecting both these issues, additional regressions have been run with recruitment during the two years prior to the start of the reference period in 2006 excluded from all inflow intensity indicators.

The results reported in Table A1 in the Appendix shows that this increase in the time lag between measured inflow and observed performance from three years in the main analysis (inflow measured throughout 2005; performance observed in 2008) to five years does not structurally alter the findings that speak to the seven hypotheses. However, the statistical significance of the coefficient for the interaction between HIGHTECH and SAME is lost at $p = 0.121$. In the estimation of the innovation activity decision, only the positive estimate for unrelated recruitment and the negative estimate for residual recruitment remains significant. This suggests that the decision to engage, or not to engage, in innovation during the CIS reference period is reflected in recruitment decisions before the start of this period in a manner that biases the estimates for RESEARCH and SAME in Model 1. Yet, this has no immediate implications for the hypotheses that are considered herein.

Furthermore, the regressions have also been estimated on a sample that include only manufacturing firms. This reflects the question raised by Timmermans and Boschma (2014) as to whether firms in services exhibit specific forms of inflow sensitivity, and is done to ensure that findings are not biased by the assumption that T-KIBS should be defined as HIGHTECH whereas P-KIBS should not. The negative interaction between HIGHTECH and UNRELATED remains in this test, but significance is lost at lost at $p = 0.232$. On the other hand, a significantly negative estimate is now obtained for the interaction between HIGHTECH and RELATED. Combined, this is interpreted as conditional support for Hypothesis H7, and underscores that certain advanced types of manufacturing are particularly dependent on high-skilled employees with strong industry-specific experiences.

A number of supplementary regressions have been run to consider the sensitivity of findings to various assumptions underlying the variables and sample used. First, inflows where depreciated by an annual rate of 15 per cent from the base year of 2006. Additional regressions estimated with depreciation rates in the range from 0 – 20 per cent find that results are not structurally sensitive to the actual rate used (cf. also Griliches and Mairesse 1984; Hall et al. 2010). Second, the maximum inflow intensity values are in the reported regressions set equal to the cut-point value for the 99th percentiles of their respective initial distributions. When the actual maximum values are used in the estimations[6], results consistent with those reported above are obtained and no substantially different interpretations are warranted.

Finally, the combination of some extreme intensity scores and rarity of certain types of inflow translate into skewed inflow distributions. We have therefore estimated regressions with

[6] The values are 2.82 for SAME, 0.82 for RELATED, 4.08 for UNRELATED and 1.33 for RESEARCH.

binary variables indicating the occurrence of inflows (e.g.Herrera et al. 2010) instead of the actual intensities. In these estimations, 78 per cent of the firms are assigned the value 1 on the binary variable representing UNRELATED. By contrast, only 37 per cent of firms are assigned the value 1 on the variable representing SAME, 36 per cent on the variable representing RELATED and 24 per cent on the variable representing RESEARCH. Beyond what is attributable to inherent differences between binary and continuous variable estimates, the results obtained are consistent with those reported above.

Discussion and conclusion

Building on recent evolutionary thinking and using a unique dataset, this paper has linked the innovation performances of Norwegian firms to their past aggregate inflows of experience-based knowledge through the labor market. By doing so, it has shown that cognitive resources and network contact points that are derivatives of the knowledge development efforts and business processes prevalent at individuals' past places of employment, over time and with consistency of exposure, may contribute to the build-up of capacity in support of innovation performance in new employer firms. Our study is therefore an important contribution to what is still an infant field of empirical research on the direct link between mobility inflows and innovation - both broadly defined. As such, it is also of high relevance to the literature on knowledge spillovers (eg. Henderson 2007), agglomeration externalities (eg. Beaudry and Schiffauerova 2009; Breschi and Lissoni 2001) and the path-dependent nature of industrial development.

Second, the study has answered the calls made for research to consider whether firms in different sectors respond differently to various inflows of experiences (Timmermans and

Boschma 2014). By doing so, it has revealed that the effects of tapping into intra-sectoral mobility flows span from strong and positive for firms that operate in technology intensive sectors, to conditionally negative when the technology intensity of the focal firms' sector is low. Moreover, it shows that the benefits of skilled labor inflows from unrelated sectors are inversely related to the technological intensity of the sector in which the recruiting firm operates, i.e. positive and strongly so for firms in low-tech industries only. This is consistent with the notion that these benefits under some circumstances are linked to the role of new employees in diversifying otherwise slow-changing and path-dependent knowledge bases, search spaces and organizational routines; whereas in other cases, they stem from the role of labor inflows in helping firms stay abreast with rapid rates of technology and market change specific to the industries in which they operate.

Third, firms in both low-tech and high-tech industries are at the outset found to benefit from recruiting at the intersection between cognitive proximity and distance; i.e. they benefit from the inflow of 'related variety'. Still, the importance of 'relatedness' is nuanced by the robustness test finding that firms in high-tech *manufacturing* industries, a small proportion of the sample, respond negatively to this type of inflow and positively only to inflows from firms in the same industry. This suggests that firms in high-tech industries are particularly dependent on locating in regions where critical mass of similar activities allow them to tap into a pool of specialized labor.

Forth, the analysis has followed Herstad et al. (2015) in considering aggregate inflows from the research system within the same empirical framework used **to** evaluate inflows from industrial sources. The results adhere to the basic evolutionary idea that the formation, diffusion and exploitation of experience-based knowledge is both cause and effect of economy-level development paths (Frenken et al. 2007; Neffke et al. 2011). By implication, innovation policies must acknowledge, and account for, the self-sustaining forces of lock-in and lock-out that arises out of the density and composition of current industrial structures to channel future development in certain directions, at the expense of others (Martin and Sunley 2006; Martin and Sunley 2010). Policies seeking to redirect development must carefully balance initiatives at the institutional level, such as research programs, university-industry linkages, technology transfer and researcher mobility; with initiatives focused on ensuring that industrial capabilities are created and grow into the critical mass that must be present in order for firms to cross-fertilize each other through the labor market (Herstad et al. 2010; Simmie 2012) Again, this particularly applies to policies seeking structural change in the direction of the advanced industrial activities that herein are captured simply as 'high-tech'.

This begs the question of whether our findings reflect poorly developed Norwegian research infrastructures and lack of alignment with industry. Still, the historical co-evolution between Norwegian incumbent industries, the dominant technical universities and the applied research institute sector (Fagerberg et al. 2009; Narula 2002; Wicken 2009a; Wicken 2009b), combined with the size and strong current dependence of the latter on the market for contractual R&D work, point to strong rather than weak alignment at the institutional level. This suggests that our findings are empirical expressions of fundamental differences between *individual* cognitions shaped by the knowledge bases and processing routines of industrial organizations, and those that are shaped by the unique and strongly institutionalized characteristics of science and education institutions (Becher and Parry 2005; Etzkowitz and Leydesdorff 2000; Herstad and Brekke 2012). These translates into a need for adaptation and even transformation of the resources that are conveyed through mobility outflow from the science system; processes that are made difficult by the very same differences in cognitions and behaviors they seek to overcome (cf. Dokko et al. 2009). Consequently, some firms may benefit from research system recruitment, and even greatly so from the contributions of individual scientists, while firms on average do not, from aggregate inflows.

It must be emphasized that the contribution from the research system to human capital formation and diffusion in society far transcend what is attributable to the aggregate outflows from prior employment that are considered herein. Universities and university colleges serve far more important roles by providing graduates with the basic cognitive skills needed to enter into and learn from various types of employment, and by developing education programs adapted to specific industry and technology needs (see Herstad and Brekke 2012 for an elaborate discussion). Our analysis acknowledges this by including only individuals with education equivalent to a BA degree or above in the intensity measures. Furthermore, as emphasized above and in the introductory section on context, Norwegian universities and research institutes serve in support of industrial innovation by conducting contractual R&D and by acting as collaboration partners to firms (Herstad et al. 2010; Narula 2002; Wicken 2009a). Because our focus has been specifically on recruitment from prior employment, and control variables have been implemented to account for other dimensions of firms' learning processes, the lack of direct effects from aggregate research system *inflows* must not be interpreted as lack of overall research system support for industrial innovation in Norway.

The analysis has not directly considered spatial aspects of mobility flows and firm responses. This is important to note, because geographical proximity to the source has been found to mediate the cognitive distances involved in recruitment from unrelated domains (Boschma et al. 2009). Specifically, and given the strong concentration of Norwegian public research institutions in a few urban strongholds (Strand and Leydesdorff 2013), this could conceal support that is provided by the research system through the labor market to firms located in their vicinity (cf. Adams 2002). Industrial activity, by contrast, is Norway more evenly distributed on different regions, and the mobility of skilled labor tend to occur most intensively within geographically confined housing and labor market regions (Eriksson et al. 2008; Eriksson 2011; Jukvam 2002). The actual composition of these regional industrial structures are therefore the single most important determinants of the recruitment channels that are readily available to firms. The main implication of this limitation is therefore that our findings represent better the performance effects that are attributable to localized mobility flows, than those attributable to flows that occur on larger geographical scales.

Moreover, the ability of the firm to respond productively to inflows requires knowledge bases and routines conducive to this task. Therefore, the baseline effects of inflows may depend on other firm characteristics that are correlated with, or directly influences, these aspects of the firm. These include general characteristics such as size, present and accumulated R&D efforts, and age. They extend into the specific composition of human resources bases in terms of educational and cultural diversity, tenure, the actual career paths or employees, and gender participation (cf. Østergaard et al. 2011). Adjacent to this is the question of whether different forms of knowledge, and, by implication, different types of aggregate labor inflow, are complementary or contradictory to each other in their influences on innovation capacity, output and performance (cf. Herstad et al. 2015). Combined, this means that complex, multi-dimensional interaction effects involving aggregate inflows *and* firm characteristics may be present that are left open by us for future research to explore.

Last, questions can be raised concerning the empirical operationalization of industry relatedness and the assumption that all types of research system recruitment can be captured by one single variable. With respect to the former, recent work has suggested that the distinctions between related and unrelated industries based on standard industry codes should be replaced with more advanced measures based on the actual mobility of skilled workers across industries (Neffke and Henning 2013). Yet, in performance analysis, these types of approaches could make the questions of reverse causality and endogeneity, discussed in the robustness test section above, more pressing. Moreover, the results that have already been obtained in empirical analysis using alternative measures (Timmermans and Boschma 2014) by and large confirm rather than challenge the main findings and substantial implications of research based on the original approach (Boschma et al. 2009) - with which the findings herein and those of other recent studies applying the original relatedness framework (Herstad et al. 2015) aligns. Last, this issue has no bearing on what is defined as recruitment from the same sector and from the research system; the results for which are central to the discussion above.

With respect to the latter, the high standard errors of the estimates for RESEARCH reveal inconsistent influences and suggests that aggregate inflows should preferably be decomposed at least by discipline and institutional source (e.g. Herstad et al. 2013). On the other hand, inconsistency is a point in itself, since RESEARCH captures the past recruitment decisions of the firm along a dimension that can be assumed to be highly selective. Moreover, the same intensity measure has previously been found to exert strong, consistent and therefore highly significant impacts on firms' patenting propensities (Herstad et al. 2015). This underscores the distinction between inventive capacities, supported by aggregate inflows from the research system, and innovative capacities, which are not - on average. Moreover, it legitimizes the use of the variable also in analysis of innovation performance. However, future work is clearly needed to investigate the specific conditions under which firms are able to identify, recruit and integrate those former research system employees that act in support of commercial innovation. More in-depth knowledge of this process is particularly important in the context of innovation policy and the design of mechanisms to lubricate it.

Based on the above, it seems unlikely that our study of aggregate labor inflows is limited in relevance by features that are unique to the Norwegian economy, or due to the specific way of operationalizing aggregate mobility inflows that has been applied; and that alternative ways of doing so on data from different countries would alter the overarching conclusion and substantial implications form our work: That innovation performance at the firm level, and innovation-based competitiveness at the level of territorial economies, is intimately interlinked with the experience-based knowledge and work practices that are endogenously created by the industrial system itself and conveyed between firms through the mobility of well-educated employees - and that this applies more so the higher the technology-intensity of involved industries is.

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Tables

Table 1: Descriptive statistics.

	Distribution of sample			Average innovation performance and inflow intensities				
Technology class	**Industry group**	ALL	ACTIVE	TURNIN	SAME	RELATED	UNRELATED	RESEARCH
Low-tech manuf.	Food & Beverages	8.5	8.1	0.111	0.005	0.007	0.027	0.001
	Textiles & Clothing	3.1	2.8	0.135	0.011	0.002	0.039	0.000
	Wood & furniture	6.0	5.6	0.082	0.005	0.004	0.027	0.000
	Pulp & paper	1.1	1.0	0.102	0.009	0.002	0.016	0.002
	Publishing and printing	6.3	4.3	0.077	**0.027**	0.011	**0.079**	0.002
	Recycling	0.6	0.5	0.016	0.003	0.000	0.054	0.002
Low-medium tech manuf.	Shipbuilding	4.5	4.0	**0.162**	0.013	0.003	0.043	0.002
	Transportation equip.	0.1	a)	-	-	-	-	-
	Rubber & plastics	2.1	2.0	0.111	0.010	0.007	0.025	0.005
	Metals & minerals	10.9	9.2	0.089	0.004	0.002	0.029	0.000
	Manufacturing nec.	0.7	0.8	**0.200**	0.008	0.000	0.057	0.001
High medium-tech manuf.	Machinery & instruments	11.1	13.3	**0.198**	0.013	0.006	**0.074**	0.005
	Automotive	1.7	1.6	**0.171**	0.011	0.001	0.031	0.002
	Chemicals	2.0	2.8	**0.171**	0.014	0.008	0.053	0.006
High-tech manufacturing	Electronics	1.3	1.9	**0.204**	**0.028**	0.005	**0.093**	**0.012**
	Pharmaceuticals	0.3	0.5	0.076	0.016	0.014	**0.119**	**0.016**
KIBS	T-KIBS	14.5	20.4	**0.258**	**0.055**	**0.043**	**0.118**	**0.020**
	P-KIBS	19.7	16.2	0.131	**0.043**	**0.028**	**0.112**	**0.011**
Natural resources	Aquaculture	1.9	1.8	0.071	0.010	0.008	0.033	0.006
	Petroleum & natural gas	3.6	3.2	0.093	**0.035**	0.006	0.071	0.006
Total		100.0	100.0	0.157	0.026	0.017	0.073	0.008
N		3197	1818	1818	1818	1818	1818	1818

Note: Only sectors represented in the sample used. a) Too few observations to permit reporting of statistics.

Note: Innovation active firms only. Performance and inflow intensities above the sample average are indicated in bold.

Table 2: Main regression results

	Baseline regression models and dependent variables		
	Model 1: ACTIVE	Model 2A: TURNIN	Model 2B: TURNIN
Firm characteristics	*Coeff (SE)*	*Coeff (SE)*	*Coeff (SE)*
AGE	-0.121***	-0.018	-0.019
	(0.043)	(0.086)	(0.087)
SIZE	0.210***	-0.178***	-0.176***
	(0.021)	(0.039)	(0.039)
GROWTH	-0.006	0.251***	0.257***
	(0.036)	(0.062)	(0.063)
MARBREADTH	1.500***	0.693***	0.718***
	(0.121)	(0.200)	(0.199)
Innovation strategy			
INNOVINT		0.206***	0.212***
		(0.028)	(0.029)
INNOEXT		-1.752***	-1.756***
		(0.314)	(0.308)
COBREADTH		0.790***	0.761***
		(0.177)	(0.174)
PRODUCT		0.018	0.024
		(0.097)	(0.096)
Recruitment intensities			
SAME	-2.717**	3.345*	1.145
	(1.184)	(1.829)	(2.046)
SAME^2	5.499	-16.406***	-21.099***
	(3.833)	(6.006)	(7.065)
RELATED	3.053	6.428**	7.083**
	(1.949)	(2.698)	(3.120)
RELATED^2	-11.906	-31.949**	-29.668**
	(10.632)	(13.291)	(13.428)
UNRELATED	4.146***	0.735	2.336
	(0.725)	(1.263)	(1.459)
UNRELATED^2	-7.026***	-1.252	-1.002
	(1.806)	(3.117)	(3.124)
RESEARCH	11.186***	3.115	4.716
	(3.858)	(5.045)	(5.666)
RESEARCH^2	-39.820	-55.698	-60.661
	(30.937)	(42.421)	(42.739)
RESIDUAL	-0.206***	-0.056	-0.385*
	(0.057)	(0.181)	(0.218)
RESIDUAL^2	0.008***	-0.001	-0.022
	(0.002)	(0.007)	(0.025)
HIGHTECH*SAME			4.374**
			(2.138)
HIGHTECH*RELATED			-1.608
			(2.776)
HIGHTECH*UNRELATED			-2.586**
			(1.076)
HIGHTECH*RESEARCH			-1.768
			(4.306)
HIGHTECH*RESIDUAL			0.651**
			(0.306)
Constant	-1.170***	-1.803***	-1.735***
	(0.198)	(0.439)	(0.449)
Estimator	Probit	Fractional logit	
Walds Chi(2)	583.52***	n.a	n.a
Df	33	37	42
AIC	n.a	0.6744	0.6765
Observations	3197 (all)	1818 (active only)	1818 (active only)

Note: Coefficient estimates and robust standard errors from probit and fractional logit regression models. *** p<0.01, ** p<0.05, * p<0.1. **All regressions include 19 industry dummies that are jointly significant.**

Table A1: Robustness test regression results #1. Only inflows throughout 2003 included.

	Regression models and dependent variables		
	Model R1_1: ACTIVE	Model R1_2A: TURNIN	Model R1_2B: TURNIN
Firm characteristics	*Coeff (SE)*	*Coeff (SE)*	*Coeff (SE)*
AGE	-0.133***	-0.056	-0.055
	(0.044)	(0.070)	(0.071)
SIZE	0.216***	-0.124***	-0.116***
	(0.021)	(0.030)	(0.030)
GROWTH	-0.015	0.174***	0.178***
	(0.035)	(0.046)	(0.047)
MARBREADTH	1.569***	0.498***	0.495***
	(0.120)	(0.153)	(0.152)
Innovation strategy			
INNOVINT		0.138***	0.141***
		(0.020)	(0.020)
INNOEXT		-1.475***	-1.460***
		(0.265)	(0.265)
COBREADTH		0.555***	0.543***
		(0.131)	(0.130)
PRODUCT		0.023	0.035
		(0.073)	(0.073)
Inflow intensities			
SAME	-1.700	2.914	1.098
	(2.025)	(2.360)	(2.914)
SAME^2	4.143	-24.020**	-34.323***
	(10.225)	(11.915)	(12.748)
RELATED	8.194**	6.258*	7.806*
	(3.881)	(3.726)	(4.345)
RELATED^2	-42.195	-71.403**	-62.205*
	(38.417)	(33.647)	(33.514)
UNRELATED	1.531**	1.219	2.952**
	(0.671)	(1.092)	(1.472)
UNRELATED^2	-0.845	-5.404	-5.546
	(3.001)	(5.074)	(4.421)
RESEARCH	14.425	-2.703	0.276
	(10.328)	(10.149)	(11.075)
RESEARCH^2	-90.732	13.558	52.201
	(177.189)	(179.130)	(182.508)
RESIDUAL	-0.295***	-0.183	-0.423
	(0.095)	(0.225)	(0.268)
RESIDUAL^2	0.020***	0.004	-0.018
	(0.007)	(0.014)	(0.047)
HIGTEHCH*SAME			4.491
			(2.893)
HIGHTECH*RELATED			-3.954
			(3.105)
HIGHTECH*UNRELATED			-2.626*
			(1.453)
HIGHTECH*RESEARCH			-8.407
			(6.794)
HIGHTECH*RESIDUAL			0.558
			(0.385)
Constant	-1.121***	-6.390***	-6.423***
	(0.196)	(0.349)	(0.358)
Estimator	Probit	Fractional logit	
Walds Chi(2)	535.06***	n.a.	n.a
Df	33	37	42
AIC	n.a.	.0613	.0668
Observations	3197	1818	1818

Note: Coefficient estimates and robust standard errors from probit and fractional logit regression models. *** p<0.01, ** p<0.05, * p<0.1. **All regressions include 19 industry dummies that are jointly significant.**

Table A2: Robustness test regression results #2. Only manufacturing firms included.

	Regression models and dependent variables		
	Model R2_1: ACTIVE	Model R2_2A:TURNIN	Model R2_2B: TURNIN
Firm characteristics	*Coeff (SE)*	*Coeff (SE)*	*Coeff (SE)*
AGE	-0.061 (0.053)	0.032 (0.103)	0.034 (0.103)
SIZE	0.287*** (0.028)	-0.086* (0.049)	-0.084* (0.049)
GROWTH	-0.077 (0.049)	0.233*** (0.082)	0.222*** (0.085)
MARBREADTH	1.398*** (0.149)	0.387 (0.258)	0.389 (0.257)
Innovation strategy			
INNOVINT		0.260*** (0.045)	(0.047) -1.509***
INNOEXT		-1.542*** (0.393)	(0.382) 0.684***
COBREADTH		0.701*** (0.222)	(0.217) 0.062
PRODUCT		0.044 (0.122)	(0.121) 0.034
Inflow intensities			
SAME	-1.145 (2.009)	7.038** (3.454)	3.764 (3.603)
SAME^2	1.670 (7.403)	-47.069*** (14.206)	-59.074*** (14.679)
RELATED	4.676 (4.058)	9.542 (6.362)	18.446** (7.483)
RELATED^2	-9.620 (26.391)	-79.605* (42.788)	-111.559** (50.237)
UNRELATED	6.342*** (1.046)	2.984 (1.839)	3.668* (1.980)
UNRELATED^2	-13.357*** (2.979)	-4.049 (4.608)	-0.937 (5.225)
RESEARCH	13.640* (7.630)	3.928 (9.832)	1.623 (11.143)
RESEARCH^2	-56.973 (61.151)	-92.128 (104.025)	-121.379 (105.459)
RESIDUAL	-0.009 (0.102)	0.250 (0.529)	-0.047 (0.546)
RESIDUAL^2	-0.003 (0.015)	-0.390 (0.278)	-0.286 (0.274)
HIGTEHCH*SAME			8.309** (3.997)
HIGHTECH*RELATED			-19.728** (9.220)
HIGHTECH*UNRELATED			-2.417 (2.049)
HIGHTECH*RESEARCH			5.677 (11.218)
HIGHTECH*RESIDUAL			0.382 (0.366)
Constant	-1.784*** (0.233)	-2.506*** (0.557)	-2.449*** (0.557)
Estimator	Probit	Fractional logit	
Walds Chi(2)	404.10***	n.a	n.a
Df	31	35	40
AIC	n.a	.6315	.6363
Observations	2104	1153	1153

Note: Coefficient estimates and robust standard errors from probit and fractional logit regression models. *** p<0.01, ** p<0.05, * p<0.1. **All regressions include 17 industry dummies that are jointly significant.**

Table A3: Descriptive statistics and correlations

	Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	TURNIN	0.157	0.249	0	1	1													
2	HIGHTECH	0.405	0.491	0	1	0.224	1												
3	AGE (log)	2.679	0.604	1.609	3.689	-0.092	-0.151	1											
4	SIZE (log)	3.800	1.323	1.609	9.842	-0.119	-0.094	0.156	1										
5	GROWTH	0.255	0.703	-0.375	3.1	0.100	0.042	-0.200	-0.018	1									
6	MARBREADTH	0.483	0.240	0	1	0.187	0.180	-0.011	0.119	0.027	1								
7	INNOVINT	1.019	1.674	0	6.21	0.370	0.315	-0.138	-0.192	0.049	0.212	1							
8	INNOVEXT	0.296	0.212	0	1	-0.240	-0.194	0.041	-0.009	0.032	-0.209	-0.219	1						
9	COBREADTH	0.160	0.256	0	1	0.167	0.010	0.024	0.168	-0.007	0.215	0.242	-0.160	1					
10	PRODUCT	0.342	0.475	0	1	0.107	0.122	-0.053	-0.086	0.031	0.101	0.172	-0.118	0.010	1				
11	SAME	0.026	0.061	0	0.383	0.032	0.121	-0.209	0.033	0.159	0.047	0.124	0.007	0.002	0.059	1			
12	RELATED	0.017	0.039	0	0.232	0.099	0.171	-0.169	-0.041	0.052	0.043	0.168	-0.038	-0.011	0.128	0.222	1		
13	UNRELATED	0.073	0.093	0	0.512	0.117	0.187	-0.194	-0.126	0.110	0.051	0.217	0.009	-0.011	0.110	0.233	0.204	1	
14	RESEARCH	0.008	0.024	0	0.156	0.080	0.171	-0.111	-0.105	0.019	0.074	0.297	-0.036	0.123	0.049	0.163	0.149	0.081	1
15	EXPOSURE	0.566	0.877	0	31.351	-0.043	-0.077	-0.059	-0.081	0.036	-0.023	-0.062	0.093	-0.048	-0.065	0.149	0.131	0.152	0.077

Note: Innovation active firms only. N=1818

Figures

Figure 1: Predicted innovation performance and marginal effects (p < 0.1 | p > = 0.1), recruitment from the research system. Computed based on Model 2A (ALL) and Model 2B (LOWTECH vs. HIGHTECH).

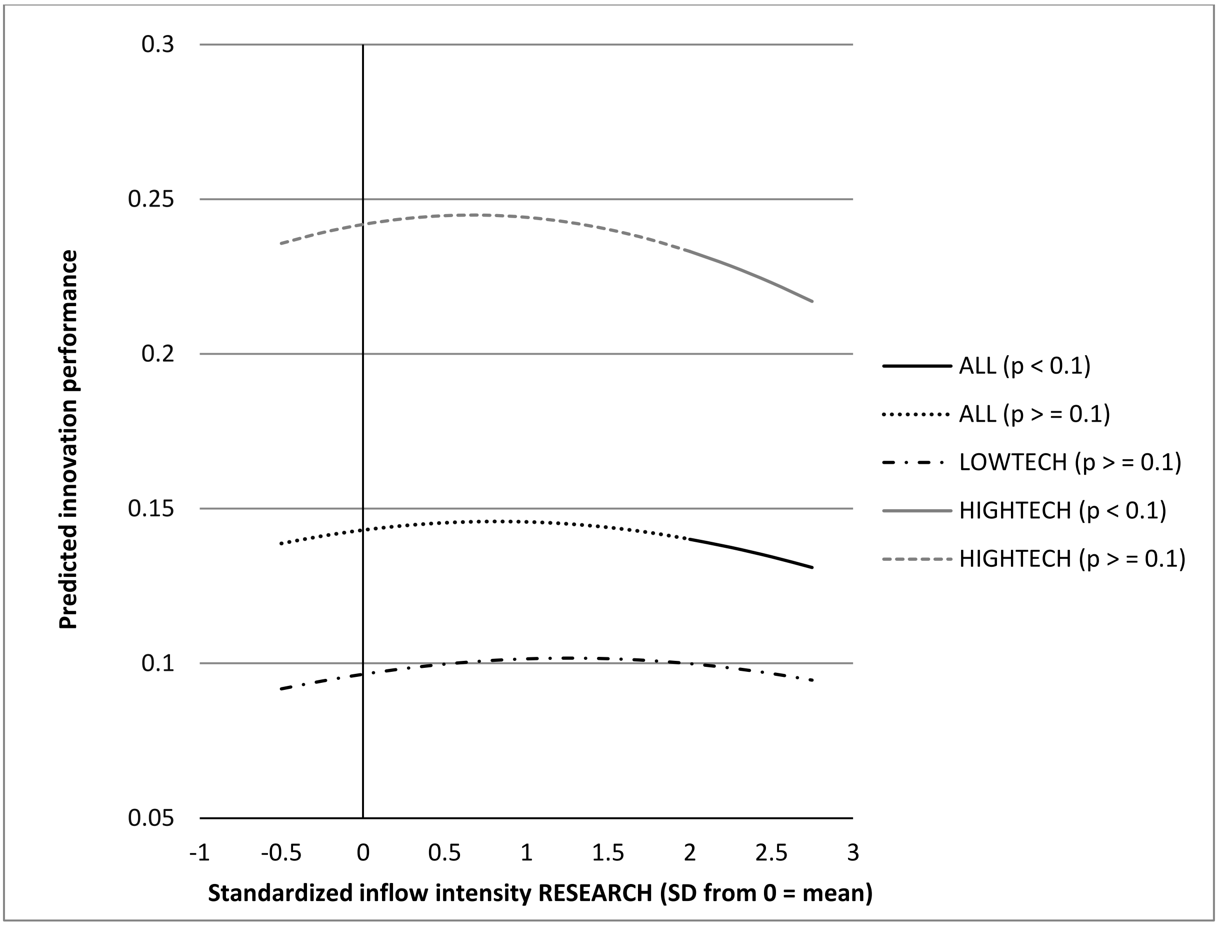

Figure 2: Predicted innovation performance and marginal effects (p < 0.1 | p > = 0.1), recruitment from the same (NACE 5-digit) sector. Computed based on Model 2A (ALL) and Model 2B (LOWTECH vs. HIGHTECH).

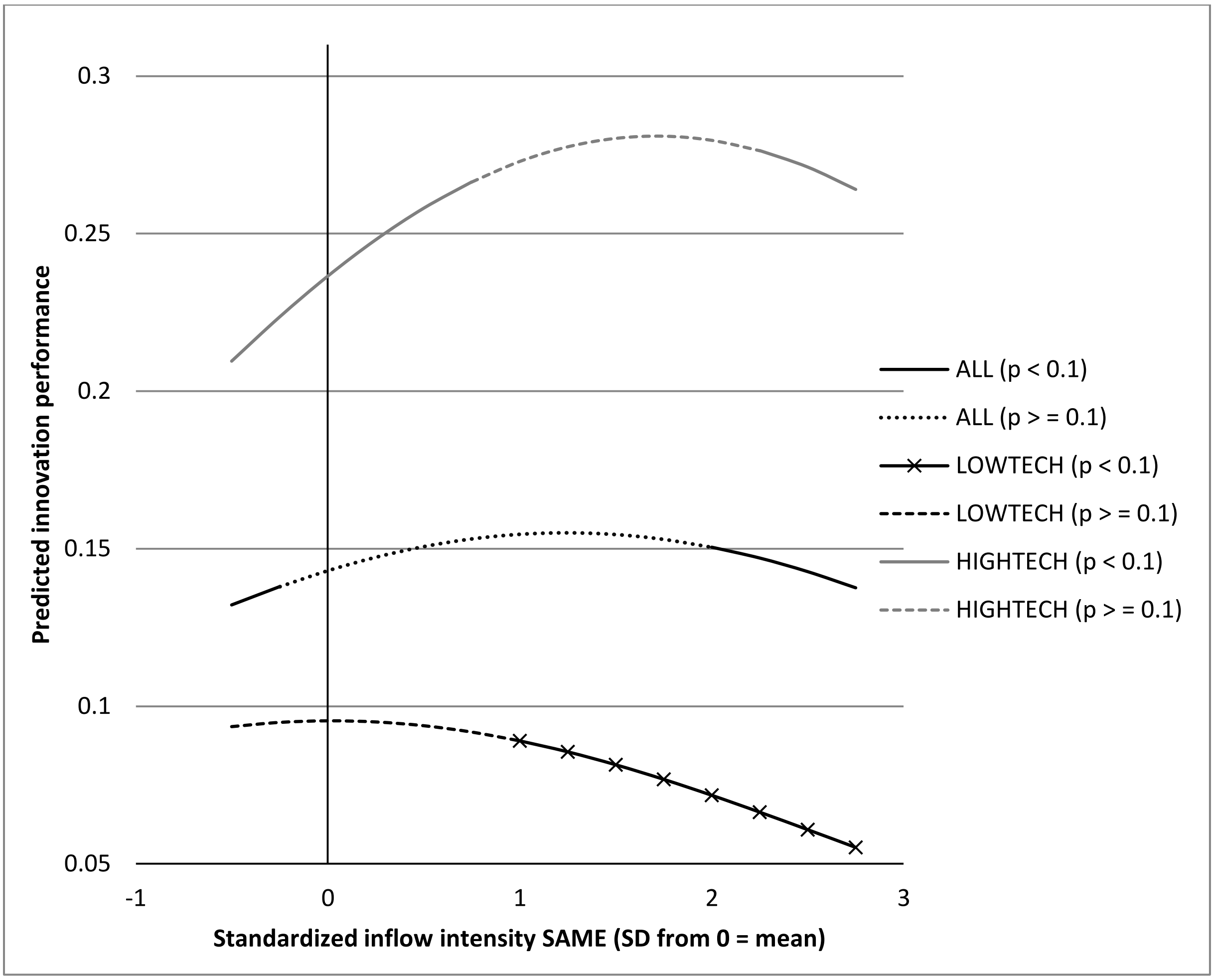

Figure 3: Predicted innovation performance and marginal effects (p < 0.1 | p > = 0.1), recruitment from unrelated (different NACE 2-digit) sectors. Computed based on Model 2A (ALL) and Model 2B (LOWTECH vs. HIGHTECH).

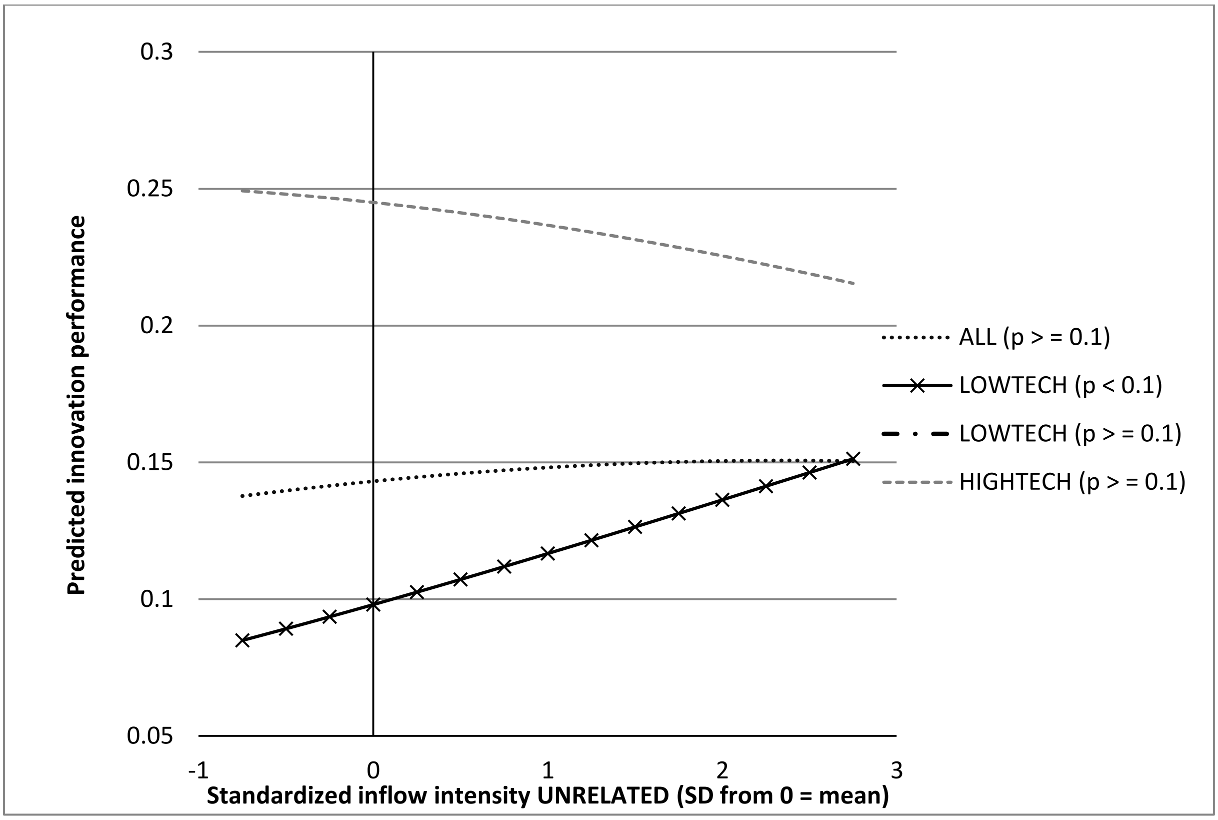

Figure 4: Predicted innovation performance and marginal effects (p < 0.1 | p > = 0.1), recruitment from related (same NACE 2-digit, different NACE 5-digit) sectors. Computed based on Model 2A (ALL) and Model 2B (LOWTECH vs. HIGHTECH).