Innovation and corporate employment growth revisited

Sverre J. Herstad (sverre.herstad@nifu.no)
NIFU Nordic Institute for Studies in Innovation, Research and Education, Oslo

Tore Sandven (tore.sandven@nifu.no)
NIFU Nordic Institute for Studies in Innovation, Research and Education, Oslo

This version: February 2015

Innovation and corporate employment growth revisited

Sverre J. Herstad and Tore Sandven

Abstract

Using Norwegian Community Innovation Survey (CIS) data linked to public employment registers covering the years 2004 - 2010, this paper investigates the relationship between employment growth prior to the event of innovation, innovation output, and growth performance after the event. Positive growth ex ante generally strengthens growth ex post. Moreover, it increases the likelihood that innovations are introduced during the intermediate period that strengthen employment performances further. This effect is present for all levels of growth only when new products, production processes and support functions are introduced in tandem. Standalone improvements of products, by contrast, influence only the probability of survival, whereas standalone improvements of production processes and support functions support ex post growth specifically in the upper tail of the distribution. Our findings challenge the common view that product innovations are more important to growth than process innovations, and reveal interdependencies between multi-faceted organizational capabilities, innovation output and employment performance.

JEL codes: J23, J24, O15, O33

Keywords: Capabilities, innovation, employment growth, Norway

Innovation and corporate employment growth revisited

Sverre J. Herstad
NIFU Nordic Institute for Studies in Innovation, Research and Education
PO Box 5183 Majorstuen, N-0302 Oslo

Corresponding author.
Mail to: sverre.herstad@nifu.no
Telephone: + 47 22 59 51 00

Tore Sandven
NIFU Nordic Institute for Studies in Innovation, Research and Education
PO Box 5183 Majorstuen, N-0302 Oslo

December 2014

Abstract

Using Norwegian Community Innovation Survey (CIS) data linked to public employment registers covering the years 2004 - 2010, this paper investigates the relationship between employment growth prior to the event of innovation, innovation output, and growth performance after the event. Positive growth ex ante generally strengthens growth ex post. Moreover, it increases the likelihood that innovations are introduced during the intermediate period that strengthen employment performances further. This effect is present for all levels of growth only when new products, production processes and support functions are introduced in tandem. Standalone improvements of products, by contrast, influence only the probability of survival, whereas standalone improvements of production processes and support functions support ex post growth specifically in the upper tail of the distribution. Our findings challenge the common view that product innovations are more important to growth than process innovations, and reveal interdependencies between multi-faceted organizational capabilities, innovation output and employment performance.

Keywords: Capabilities, innovation, employment growth, Norway
JEL: J23, J24, O15, O33

1. Introduction

The contribution of firms to economic growth and welfare is directly related to the number and quality of jobs that they provide. Thus, the ability of economies to sustain high levels of well-paid employment is the primary benchmark for their performances (Herstad, 2011, pp. 142-143). Due to increasing international competition and rapid rates of technological change, this ability is assumed to depend on continuous industrial renewal through innovation. Policies seeking to increase the commitment of firms to development work are therefore high on the agenda in most countries (Demirel & Mazzucato, 2014), and the study of growth has re-emerged as one of the key areas in industrial economics and management studies (Lee, 2010; Reichstein, Dahl, Ebersberger, & Jensen, 2010).

The link between technological development, innovation and employment can be studied at different levels (Mastrostefano & Pianta, 2009). Due to so-called business stealing effect whereby labor is shifted between firms, some argue that the effects of innovation on employment cannot be captured at the firm level. Thus, they call for empirical studies of net employment effects at higher levels of aggregation, such as industries, regions or countries (Greenan & Guellec, 2000). Others believe that knowledge of the conditions under which some firms expand while others decline, remains of vital importance to the understanding of aggregate-level industrial dynamics (Cefis & Orsenigo, 2001; Alex Coad & Rao, 2008; Nightingale & Coad, 2014). Our study adheres to the latter view. This is primarily for theoretical reasons that are elaborated below, but also because the Norwegian economy from which our empirical data is drawn has operated at exceptionally high aggregate levels of employment during the period that the data cover (Herstad & Sandven, 2014b).

The ability of firms to reflect evolving market demand and technological opportunities through innovation is as much an organizational capability, embedded in their routines and knowledge bases and expressed as 'bundles' of commercial output (Kogut & Zander, 1992; Piening & Salge, 2014), as it is a technical capacity, contained within R&D departments and expressed e.g. through patent output (Herstad, Sandven, & Ebersberger, 2015). This is evident from the substantial proportion of innovative firms that do not engage in systematic R&D (Herstad & Brekke, 2012; M. B. Jensen, Johnson, Lorenz, & Lundvall, 2007), and the large proportion of patents that are idle (Arundel & Kabla, 1998; Gambardella, Giuri, & Luzzi, 2007). Still, there is a clear tendency in the empirical literature to use R&D investments and patent output to proxy innovation (Alex Coad & Rao, 2008; Del Monte & Papagni, 2003; Demirel & Mazzucato, 2014). Studies of growth that have used dedicated innovation surveys to move beyond these confines have emphasized the importance of new product introductions,

in particular when paralleled by process innovations (Evangelista & Vezzani, 2010). Yet, these studies have often considered growth during the limited periods of time during which innovation is also observed. Consequently, important questions concerning the direction of causality, and of simultaneity biases due to the temporal proximity of independent and dependent variables, are left open.

The following seeks to circumvent these limitations. Using concepts drawn from resource-based theories of the firm (Leonard-Barton, 1992; Teece, Pisano, & Shuen, 1997; Wernerfelt, 1984), we first discuss the organizational characteristics that lie at the heart of firms' innovation capacities, and how these capacities evolve cumulatively, in interaction with technological opportunities and market demand. The empirical analysis is based on Norwegian Community Innovation Survey from 2008 (CIS2008) and annually updated public register data on employment. This has allowed us to construct a dataset consisting of firms with known innovation output characteristics during the three-year reference period of 2006-2008, and observable growth before and after this period. Based on this, we investigate in detail how ex ante growth trajectories influences the propensity of firms to patent and introduce different types of innovations, and how the composition of this innovation output is associated with *ex post* survival probabilities and employment growth.

2. Innovation capacity and employment growth

There is a longstanding tradition in the literature on growth of framing the question of impacts from technological change within the context of 'optimizing' capacity responses to innovations that are treated as exogenous to the larger human resource bases of firms (Piening & Salge, 2014). This forces a strong focus on how different types of innovations contribute to shifts in supply and demand curves, and in this way trigger adjustments of overall capacity and employment. By developing and introducing new products, firms can reduce competitive pressures and become more detached from prevailing market prices and the behavior of competitors (Smolny, 1998). This allows increases in output and employment, but may also, depending on the strategy of the firm and the competitive condition faced, result in reduced production volumes at higher unit prices and lower employment levels (Hall, Lotti, & Mairesse, 2008). Such displacement effects of innovation on employment are expected to be particularly strong in the case of process innovations, as they are assumed to involve substitution of labor with capital equipment. Still, it is also acknowledged that reductions in the effective cost of labor allow firms to lower prices and achieve sufficiently

higher output (cf. Harrison, Jaumandreu, Mairesse, & Peters, 2008) for employment levels to increase.

Resource-based theories of the firm (Penrose, 1959; Wernerfelt, 1984), by contrast, conceptualizes employment performance as intimately interlinked with the ability of firms to exploit the resources that are continuously created through their business processes, and embedded in their workforces and organizational routines (Leonard-Barton, 1992; Wang, He, & Mahoney, 2009). Rather than taking the perspective of specific products and markets, and then ask what scale and scope of activity in these markets that maximizes profits, it takes the perspective of firms-specific resources and ask what products, market presences and business models that are necessary to exploit and expand these resources further. This ability to 'integrate, build, and reconfigure internal and external competences' is now commonly referred to as 'dynamic capabilities' (Teece & Pisano, 1994; Teece et al., 1997). These capabilities are embedded in various, interrelated activities directed at generating, acquiring, integrating and disseminating different types of knowledge (Barbero, Casillas, & Feldman, 2011; Ebersberger & Herstad, 2011; Leonard-Barton, 1992; Roper, Du, & Love, 2008), and are most clearly expressed as streams of complementary innovation outputs (Piening & Salge, 2014).

The relevance of this view is underscored by a stream of recent contributions that have found interdependencies and complementarities to characterize the relationship between different types of innovation activities, various types of output, business models and corporate strategy (Cassiman & Veugelers, 2006; Ebersberger & Herstad, 2011; Grimpe & Kaiser, 2010; Roper et al., 2008). Product innovations are in this perspective important due to the direct effect of new products on market demand, but also due to the complementary changes in organizational structures, production processes and support functions that are commonly initiated, and often required, as firms work on exploring the interfaces between markets and technological opportunities (Dougherty, 1992). Similarly, process innovations do not simply involve substitution of labor with capital. Rather, they represent changes in 'the ways things are done' (Piening & Salge, 2014) that may have strong implications for knowledge mobilization and integration capacities 'upstream' in the development process (Macher & Mowery, 2009), and for the 'downstream' capacity of firms to capitalize on the innovations that are introduced.

Consistent with this, a recent empirical study found process innovations to be intimately linked to the breadth of other innovation activities, and their profitability to be mediated by other outcomes of development work than cost savings (Piening & Salge, 2014), for instance,

improvements of product quality. Moreover, the growing importance of 'mass customization' (Pine, 1993), wherein advanced, flexible production processes allow firms to tailor even small product batches to individual customer needs without substantial increases in unit costs, substantially tightens the interpdendencies between products, production processes, logistics systems and business models (Fogliatto, da Silveira, & Borenstein, 2012; Zahra & Nielsen, 2002; Zhong, Dai, Qu, Hu, & Huang, 2013). Last, employment growth itself, irrespective of underlying causes, inevitably forces the firm to rethink the way things are done due to associated increases in organizational scale and complexity; and due to large-scale exposure to competences and work-practices that reflect the past work-life experiences of new employees (Dokko, Wilk, & Rothbard, 2009; Herstad et al., 2015; Singh & Agrawal, 2011; Timmermans & Boschma, 2014).

In this perspective, innovation output influences the firms' business activities, competitiveness and potential for employment growth in two fundamental ways: First, a direct effect that operates through external market responses to specific innovations that are introduced, and feed back to the firm as incentives to adjust capacity to new yet temporary profit-maximizing levels. Second, through indirect effects that are knowledge accumulation, adjustments of routines and external network reconfigurations triggered by the development work itself (Dougherty, 1992; Ebersberger & Herstad, 2011), which moderates or reinforces the direct effects. The actual interplay between direct and indirect effects are dependent on the capital market incentives and constraints that the firm operates under (Aglietta & Breton, 2001; Thorsten Beck & Levine, 2002; T Beck, Levine, & Loayza, 2000; Carpenter, Lazonick, & O'Sullivan, 2003), and on management attention and preferences towards either one effect (Ocasio, 1997). Differences in how this interplay materializes is evident from the fat-tailed distributions that are often observed (Bottazzi & Peri, 1999; Reichstein et al., 2010; Reichstein & Jensen, 2005). Also, it is evident from positive autocorrelation of growth rates for firms with strong resources positions, and as particularly noisy growth in those subsamples of firms wherein heterogeneity in the strength and characteristics of resources and capabilities is highest at the outset, i.e. among small firms (A Coad, 2006) or firms that are young.

The resource-based view of the firm is closely associated with an evolutionary understanding of aggregate-level industrial dynamics, wherein the market environment itself and the knowledge and business practices that firms draw upon in their efforts aimed at relating to it, are considered endogenous to the competitive process, i.e. constructed by firms collectively through their individual efforts (Smolny, 1998). If more and more firms become

active product innovators, price competition is displaced by innovation-based competition as each firm seeks protection from the behavior of competitors through the uniqueness of their products and production processes (ibid). This increases the importance of firm-specific resources and capabilities. Furthermore, the combined efforts of firms that individually aim at product diversification, improvements of production processes and the implementation of new business models results in an ever-expanding stock of more and more diverse knowledge and organizational practices available as inputs for further development work to build on (Grossman & Helpman, 1991). These resources diffuse between firms through labor market mobility (Balsvik, 2011; Breschi & Lenzi, 2010; Eriksson, 2011), and are systematically exchanged through production networks, inter-firm technology trade (Hauknes & Knell, 2009) and innovation collaboration (Herstad, Aslesen, & Ebersberger, 2014; Tether, 2002).

Consequently, rather than studying R&D, other dedicated innovation activities or specific output in isolation, an integrative perspective on the contribution of various, often distributed, business functions, competences and external networks to complex and cumulative development work resulting in interrelated innovation outputs is necessary. This has substantive as well as methodological implications. The main substantive implication is that the productivity of R&D in terms of commercial novelty output is dependent on broader range of organizational resources and capabilities than can be contained within R&D departments or project groups (Grant, 1996). Moreover, it is dependent on the internal routines and communication systems that allow mobilization, coordination and integration of these resources into development work without costly errors and misunderstandings between departments and areas of responsibility (Ebersberger & Herstad, 2011; Foss, Lygsie, & Zahra, 2013; Hoopes & Postrel, 1999).

Against this background, it is not surprising to find the link between R&D investments and growth to be conditional. In a recent study of start-ups, R&D is found to differentiate the actual growth rates of firms only amongst strong growth performers, and the effect to be dependent on their external partner networks, i.e. to be strongest amongst firms that have already established strong resource and network positions (Stam & Wennberg, 2009). Using a very different sample consisting of top European R&D spenders, García-Manjón & Romero-Merino (2008) find the effect of R&D intensity on growth to be strongest in high-tech sectors, i.e. in sectors wherein the R&D content is high by definition, and among strong growth performers (García-Manjón & Romero-Merino, 2012). In a similar vein, Coad & Rao (2008) find the common variance of R&D intensity and patent output to influence growth only in the upper percentiles of the growth performance distribution, whereas Demirel &

Mazzucato (2014) find R&D to boost firm growth in the US pharmaceutical sector only when firms are small and have patented persistently for a minimum of five years. For larger firms, they indicate the effect of R&D may be negative.

The main methodological implication is that the empirical link between capabilities, innovation and growth should be made using information on the commercial innovation output of firms, because it is the composition of this output that most reliably expresses the resources and organizational capabilities that, in the last instance, are of interest. Acknowledging this, Evangelista and Vezzani (2010) uses the Italian CIS3 cross-section to find that innovation strategies expressed through simultaneous product development, process improvement and broader processes of organizational change are necessary for firms to achieve a 'true' competitive advantage (Evangelista & Vezzani, 2010, p. 1261). Earlier work on Italian data by Hall and colleagues did not consider organizational innovation specifically, but emphasized the contribution of product innovation to employment growth (Hall et al., 2008). Findings consistent with these on the importance of product innovation have been obtained using firm samples that span from small firms in Northern England (Freel & Robson, 2004) to manufacturing firms in Brazil (Goedhuys & Veugelers, 2012) and business services firms in the US (Mansury & Love, 2008).

While there are exceptions to this, e.g. in the work of Hall and colleagues (2008), these studies have commonly used dedicated innovation survey data to capture innovation output and growth during limited, overlapping periods of time. From this, questions arise concerning the direction of causality, and of whether the 'real' long-term implications for growth are over-estimated or under-estimated. Actual impacts may be overestimated if firms increase employment in support of the development work itself, and, contrary to what resource-based theories postulate, adjusts back to the initial level of employment once the work has been finalized and innovations have been introduced. They may be underestimated if long time-spans are needed to convert novel products and production processes, and the larger process of organizational change that are assumed to be initiated by their development, into measurable employment performance (cf. in particular Geroski, Machin, & Reenen, 1993).

In the following, we seek to contribute new insights into these issues. In order to do so, we have constructed a representative firm-level dataset with characteristics approximating that of a panel. This dataset allows i) the composition of innovation output during a certain period of time to be observed in accordance with the base theory laid out above, ii) regressed on observable ex ante (prior to innovation) growth rates and iii) used as explanatory variables in estimations of growth ex post.

3. Data, variables and methodological approach

3.1. Data

The analysis is based on the Norwegian firms sampled in the sixth round of the pan-European Community Innovation Surveys (CIS2008). In contrast to many other European countries, participation in the survey was compulsory. This resulted in a comparatively large data set, which is not plagued by a non-response bias. The full CIS2008 consists of 6029 enterprise-level observations, and provide information on their innovation activities and outcomes during the reference period 2006-2008. To ensure that the period for which innovation is observed and growth rates are computed is the same for all firms, the data used herein is restricted to the 4604 enterprises that had more than 10 employees or more in the sampling year (2008) and existed the entire survey reference period. The data cover natural resource based industries, manufacturing industries, construction and infrastructure provision, wholesale, traditional professional services and new technology based services. Prior to release for research purposes, the data were thoroughly reviewed and validated by Statistics Norway.

Additional information gathered from public business registers for the years 2004-2006 (the two-year period prior to the three-year survey reference period) and 2008-2010 (the two-year period after the end of the reference period) has been used to compute growth. This gives the sample characteristics that approximate those of a panel, yet deviates from panel data in three important ways. First, it includes new entrants during the two-year period 2004-2006 for which actual ex ante (2004-2006) growth rates for cannot be computed. Second, it includes firms sampled in the CIS2008 that exited from the registers in the period 2008-2010, i.e. were closed down after the end of the CIS reference period, but prior to the end year for the growth computation. Third, we cannot directly observe innovation output prior to 2006, or after 2008.

3.2. Growth

Our main interest is in the ex post growth performance of firms, which is computed from the start of the CIS2008 reference period in 2006, until 2010, i.e. two years after the end of the period during which innovation is observed. Using the start year 2006 as the base year for the computation is necessary because we cannot determine exactly when, during the period 2006-2008, innovations were actually launched. The rate is represented in the analysis by the

categorical ordered dependent variable EXPOST. Compared to the use of a continuous growth measure, as is common in the literature, the categorical variable circumvent estimation problems due to the non-normality of the growth distribution and allows us to treat survival from 2008 to 2010 as an integral component of the larger growth construct.

EXPOST takes on the value 0 for firms that exited the registers during the two years following CIS sampling. These constitute 5.5 per cent of the sample. For the remaining 94.5 per cent of the sample, the actual growth rate has been computed as the log of employment in 2010 minus the log of employment in 2006[1] (A Coad, 2006; Alex Coad & Rao, 2008; García-Manjón & Romero-Merino, 2012). The observations have then been divided into equal categories ranging from 1 (lowest 20 per cent of the growth distribution) to 5 (highest 20 per cent of the distribution). The distribution of firms across these categories where then adjusted so that EXPOST > 2 equals the lowest levels of positive growth detected in the sample, and to ensure that the lower cut-point value of any category is always equal to the first growth score that is higher than the highest score in the category below[2]. Cut-point values for the different categories and the distribution of the sample is given in Table 1 below.

Table 1 approximately here

There are two main reasons why growth ex post innovation cannot be understood independently of growth ex ante. First, because prior growth may influence later growth through autocorrelation (A Coad, 2006; Piening & Salge, 2014). Second, because prior growth is associated with firm strategies and resource positions, and may thus influence the propensity to innovate. The growth of firms prior to the start of the CIS reference period, i.e. from 2004 – 2006, is captured by the categorical variable EXANTE, which is designed to mirror EXPOST. It takes on the value 0 for firms that where established during the 2004-2006 period. For all other firms, growth is computed as above and firms distributed on five categories that span from 1 (lowest 20 per cent of the distribution) to 5 (highest 20 per cent). The cut-point values are adjusted as described above. In the regressions, this variable is represented by a set of dummies that are compared to a reference group consisting of the

---

[1] This equals the log of the ratio ln(employment 2010 / employment 2006)
[2] Due to this procedure, observations are not perfectly evenly distributed on the different categories. Without this procedure, some firms exhibiting the same growth would be have been assigned to different growth categories.

firms that where founded during the three-year period in question (EXANTE_NEW). The use of dummy variables allows us to treat new firm formation as integral to the ex ante growth construct, and account for potential non-linearity.

3.3. Innovation

The CIS questionnaire ask firms to specify whether, during the reference period, they introduced i) new or significantly improved products (goods or services) onto the market; or ii) implemented a new or significantly improved production process, support functions or means of storage and delivery. At the outset, we therefore have two main types of commercial innovation output (PRODUCT and PROCESS). Note that the definition of a 'product innovation' includes both goods and services and that the definition of a 'process innovation' is not purely technological but refers also the larger organizational systems that surrounds and support production. Following Herstad et al (2015), we also use the variable PATENT as an indicator of technological inventive capacity. The variable takes on the value 1 if the firm submitted a patent application during the years 2006-2008.

Three conditional outcomes can be identified based on this, which serve as the main explanatory variables in the growth regressions. The variable PROD_ONLY takes on the value 1 if the firm stated that it introduced a new product onto the market, but did not improve its production process. Similarly, the variable PROC_ONLY takes on the value 1 if the firm stated that it significantly improved its production processes, yet did so without a new product launch. Last, the variable BOTH captures product introductions in tandem with process innovations, as broadly defined herein. These variables allow us to disentangle whether capabilities and strategies associated with the two different types of output (PROD_ONLY; PROC_ONLY) have different implications for subsequent employment changes, or, alternatively, whether employment performance is associated first and foremost with firm capabilities and strategies expressed by the co-existence of both types of innovation (BOTH).

Table 2 approximately here

The descriptive statistics and correlations given in Table 2 above shows that ex post growth is significantly and positively correlated only with BOTH, which is also the most

commonly occurring innovation output. Moreover, it is negatively correlated with the dummy variables representing the lower levels of past growth, and positively correlated with the variables capturing higher levels. This in line with empirically observed serial correlations of growth rates (A Coad, 2006), and with the related theoretical notion that growth strengthens the resource positions of firms and in this way allows them to grow further.

Ten per cent of the sampled firms applied for a patent during this period, but these applications are not significantly correlated with growth. Yet, they are correlated with BOTH and PROD_ONLY. This legitimizes the attention paid to isolating the effect of technological novelty content and IPR protection (PROPAT) from the effect of any of the commercial innovation outcomes.

3.4. Control variables

The relationship between growth and firm size has been discussed intensively since Gibrat proposed that growth, on average, is proportional to current size (Gibrat, 1931). Several studies conducted during the large-firm dominated growth regime of the postwar period (cf. Herstad, 2011) support what has become known as Gibrat's Law (see Reichstein et al., 2010; Sutton, 1997 for reviews). Other, more recent studies suggest that firm growth is negatively correlated with size (Dunne & Hughes, 1994; Evans, 1987; Reichstein & Jensen, 2005). Partly in response to this discussion, we include the logs of firm size in 2004 and 2006 as controls in Model 1 (the probability of innovation) and Models 2 – 6 (the probability of growth) respectively. In the latter, they are included also to capture the likely relationship between size and survival (GROWTH_0610 > 0), and to avoid that expected associations between size in 2006 and innovation output in the three-year period that follows confound the relationship between this innovation output and growth ex post.

The presence of employees with MA education or above has previously been shown to influence survival and growth probabilities (Herstad, Sandven, & Solberg, 2013), as well as innovation propensities (Herstad & Sandven, 2014a). Following Piening and Salge (2014), the proportion of employees who have higher education (HIGHED) is therefore included to control for the composition of the firms' human resource base at the start of the CIS2008 reference period in 2006.

The propensity to innovate, the types of innovation launched and the probability of employment growth differ substantially between industries. Specifically, the last decade has seen a strong increase in services employment, wherein innovation rates generally are lower

than within the manufacturing industries that in relative terms have been shrinking. To ensure that this does not bias the relationship between innovation capacity and employment at the firm level, 15 dummy variables capturing industry groups are included in the regressions.

3.5. Estimation strategy

The analysis is conducted in three stages. First, we estimate whether the probabilities of PRODUCT, PROCESS and PROPAT during 2006 – 2008 are associated with the growth of the firm prior to this period, i.e. during 2004 – 2006. Because the three outcome variables cannot be assumed independent of each other (Herstad et al., 2015), they are estimated simultaneously using the multivariate probit estimator (Cappellari & Jenkins, 2003; Chib & Greenberg, 1998). The probabilities estimated for each of these variables are unconditional in the sense that no assumptions are made concerning the value of the other dependent variables. Since growth from 2004 to 2006 is correlated with size in 2006, this stage controls for firm size in 2004 (SIZE_04 = log (1 + employment in 2004)).

In the second stage, we are interested in how the ordered categorical variable that describes growth ex post is associated with resource positions and capabilities that are expressed partly through the ex ante growth rate of the firm, and partly through its innovation output. Because we want to isolate the two effects from each other, we estimate how the three possible conditional innovation outcomes PROD__ONLY, PROC_ONLY and BOTH influences EXPOST when controls are included for growth ex ante to capture autocorrelations (A Coad, 2006; Piening & Salge, 2014). Size effects are here captured by the log of firm size in 2006 (SIZE_06), i.e. at the beginning of the CIS reference period.

The categorical dependent variable necessitates the use of the ordered logistic regression estimator (Greene, 2000). This estimator assumes parallel regression lines, i.e. that the coefficients of the independent variables do not vary across the modalities of the dependent variable (Williams, 2006). Since a main point made in the literature is that the effects of different explanatory variables on growth may vary across the growth distribution (Alex Coad & Rao, 2008; García-Manjón & Romero-Merino, 2012; Reichstein et al., 2010; Reichstein & Jensen, 2005), violations of this assumption are to be expected and are less of a technical limitation than of substantive interest to the analysis. To acknowledge this, a Brant's tests for parallel regression lines has been conducted (Brant, 1990; Long & Freese, 2006). Reflecting the results of this test, the third stage consists of a set of binary regressions that are estimated

to consider how the variables for which the assumption is violated influences specifically the likelihood of survival (EXPOST > 0); of positive growth (EXPOST > 2) and of high growth (EXPOST > 4). Alternative estimation strategies involving the use of the Tobit estimator, Heckman selection models and quantile regressions are discussed in a dedicated section below.

4. Results

4.1. Ex ante growth and innovation

Table 3 below displays the results of the multivariate probit regression (Model 1) that estimate how the probabilities of product innovation, process innovation and patent application during 2006-2008 are associated with firm growth during the years 2004-2006. In the product innovation equation, the estimates for the dummy variables capturing different levels of growth for firms established prior to 2004 are all negative and jointly significant compared to the EXANTE_NEW reference (Walds Chi2 = 37.58***). At the outset, this simply shows that young firms are more inclined to introduce new products onto the market than are old firms. Pairwise comparisons of the coefficients for mature firms also reveal that any of the three variable indicating positive past growth (EXANTE_3, EXANTE_4 and EXANTE_5) yields estimates that are significantly different from any of the (more negative) estimates associated with the two variables indicating negative past growth (EXANTE_1 and EXANTE_2)[3]. This means that mature firms with negative past growth are the least likely to have introduced product innovations.

This pattern is present also in the process innovation equation. Again, the dummy variables capturing the growth of firms established prior to 2004 are all negative and jointly significant compared to the EXANTE_NEW reference (Walds Chi2 = 27.02***), in spite of less clearly significant individual differences towards the reference. The pairwise tests of the coefficients reveal that firms which exhibited positive growth during 2004-2006 are more likely to have introduced process innovations in 2006-2008, than are the firms that exhibited negative growth in this period[4]. However, the estimates for the variables indicating positive past growth are *not* jointly significant from the reference (Walds Chi2 = 3.22, p = 0.3780), meaning that comparably new firms and mature firms with positive growth are as likely to

---

[3] Significance at 5 per cent level of stronger. Walds Chi2 test statistics for 2 (variables indicating negative growth) x 3 (variables indicating positive growth) = 6 pairwise tests are not reported but available from the authors upon request.

[4] See previous footnote

improve production processes, and more so than mature firms with negative past growth. This is clearly at odds with the common view of process innovations as defensive responses to troublesome market conditions.

Table 3 approximately here

Last, we consider the PROPAT equation, wherein firms established during the period 2004-2006 are found to exhibit significantly higher probabilities than firms established prior to 2004. Within the latter group, pairwise tests of the coefficients do not reveal any consistent differences between those that exhibited negative growth, and those that did not. The only significant pairwise differences are those between the highest level of ex ante growth (EXANTE_5) and the other growth classes[5]. This means that resource accumulation and market positing through past growth does in general increase the probability of later patent applications; rather on the contrary: Taken together, the findings suggests that formal IPR protection is used by new firms to compensate for their comparatively weaker organizational resource positions.

4.2. Ordered logit estimations of ex post growth

We then turn to consider how innovation output is associated with employment growth after the event. The results form Model 2, displayed in Table 4 below, suggests that growth is positively associated with all three distinct forms of innovation output, and with technical inventive capacity signaled by a patent application. Still, pairwise Walds tests reveal that the estimate for BOTH is significantly larger than the estimates for PROD_ONLY (Chi2 = 5.39**), the estimate for PROC_ONLY (Chi2 = 5.18**) and for PROPAT (Chi2 = 2.77*). This is consistent with the notion that complex, multi-faceted development work expressed empirically through complementary product and process innovations is a particularly strong foundation for employment growth. When all controls are included in Model 3, the estimate

---

[5] Threshold for significance is p < 0.1. Walds Chi2 test statistics for 10 pairwise tests are not reported but available from the authors upon request.

for BOTH remains strong, highly significant and significantly different from the estimates for the other output variables.

The Brant's test reported in the left-hand side of Table 4 consists of a set of binary logistic regression that estimate the probability of growth scores above the five threshold values that are relevant when the number of growth categories is six (Long & Freese, 2006). Based on these estimates, Chi2 tests of the variance of coefficient estimates are conducted for each explanatory variable to assess whether the parallel regression line assumption holds. The significant Chi2 test statistics reported in the left column of Table 1 for PROD_ONLY and PROC_ONLY indicate that the assumption is violated for these two variables, while the insignificance of the Chi2 test for PROPAT indicate that it is not violated in this case. The insignificance of the test statistics for BOTH entail that this output expresses capacity and strategies that matters equally to any level of growth.

Table 4 approximately here

As expected, the assumption is violated for SIZE_06 and for the dummy variables capturing past growth. A closer look at the coefficient estimates for the five binary regressions reported in the right-hand side of Table 4 shows that the relationship between SIZE_06 and survival is positive, whereas the relationship between SIZE_06 and actual growth in employment is negative. This is in accordance with expectations. The estimates for PROD_ONLY similarly suggest that innovation capacities and strategies leading to new product introductions without attention to improvements of production process and support functions increases the likelihood of survival, but not to strengthened growth. This nuances the common view that product innovation per se is of particular importance to growth, and suggests that organizational capacity dedicated primarily to this type of development work may be insufficient. For PROC_ONLY the opposite appear to be the case; as the coefficient for EXPOST > 4 is positive and substantially larger than the coefficients estimated for the same variable in any of the other binary logit models. Thus, process innovations are not only driven by strong growth ex ante (cf. Model 1), they may also strengthen employment performance ex post.

These findings are notable not only because they are consistent with the notion that the underlying capabilities construct may lead to autocorrelation between growth rates. They are

also notable because they challenge the dominant view on the relative importance of product and process innovation to employment growth. Thus, they warrant further attention.

4.3. Binary logit regressions on ex post growth thresholds

In Table 5, we display the results of three binary logistic regressions in which the probabilities for achieving growth above specific thresholds are estimated. EXPOST > 0 corresponds to the probability of survival, whereas EXPOST > 2 corresponds to the probability that employment in 2010 is higher than employment in 2006. EXPOST > 4 corresponds to the probability that the firm has placed itself in the upper 20 percent on the growth distribution for 2006-2010 (cf. Table 1). Supplementary Wald's tests have been conducted to test between-regression differences in coefficient estimates, and are reported in the left-hand column of Table 2.

In the binary estimation of survival probabilities (EXPOST > 0), PROD_ONLY yields a positive estimate that is significant in itself. However, and consistent with the Brant's test, the introduction of new products onto the market without mirroring process innovations as broadly defined herein does not influence the probability that firms achieve positive (EXPOST > 2) or high (EXPOST > 4) growth. In fact, the coefficient estimate for the latter is negative. The tests reported in the left-hand columns show that this translates into an estimated effect of PROD_ONLY on the probability of survival that is significantly stronger than the estimated effects of PROD_ONLY on positive growth. This indicates that the introduction of new products without any other forms of innovation is associated with firm strategies and capabilities that favor focused innovation strategies over the development of more complex organizational capabilities, and that this comes at the expense of employment growth.

Table 5 approximately here

The introduction of new production processes or support functions without parallel product innovations does not significantly influence the probability of survival, nor the probability of achieving positive employment growth. However, it yields a coefficient estimate for EXPOST > 4 that is highly significant and comparable in size to the effects also

detected from BOTH and from PROPAT in this regression. Moreover, the estimate for PROC_ONLY is significantly larger in the estimation of EXPOST > 4 than in the estimation of positive growth more generally (EXPOST > 2). This is consistent with what was indicated by the Brant's test. Consequently, process innovations are not only driven by strong growth in the past; they become more important to future growth the higher the actual growth thresholds considered are.

The estimate for PROPAT is significant in Model 5 only and found to be different from the estimates obtained in Model 4. Yet, the significance of this difference is weak, and the Brant's test did not provide grounds to expect that the parallel regression line assumption be violated on a general basis. In such cases, priority should be given to the results from the overall test of variance, i.e. the Brant's test, and specific post-hoc results should not be considered further (Cody & Smith, 1991, pp. 142-143). This leaves us to conclude that technical inventive capacity and formal IPR protection signal resource positions, capabilities and strategies that does contribute on its own to employment growth, yet only moderately so.

Notable control variable influences in these regressions include the positive yet insignificant estimate for size in the estimation of survival (EXPOST > 0), compared to the negative and significant estimates for size on the probabilities of positive (EXPOST > 2) and high (EXPOST > 4) growth. Moreover, size has a significantly more negative impact on the probability of high growth, than on the probability of positive growth. This is in accordance the results from the Brant test, and, as noted above, with prior research suggesting that size moderates negative growth in the lower tail of the distribution, and positive growth in the upper tail (Reichstein et al., 2010).

Last, we turn our attention to the direct relationships between growth ex ante and ex post. Firms that were established during the years 2004-2006 and thus are comparatively immature, exhibit lower probabilities of having survived form 2008 to 2010 than any other group. This is evident from the positive estimates for all categories of prior growth, including negative growth, which are jointly significant (Walds Chi2 = 120.93***) compared to the EXANTE_NEW reference. Moreover, pairwise comparisons reveal no differences between the estimates for the different growth dummies. In the other end of the growth continuum (EXPOST > 4), we find that firms established prior to 2004, i.e. mature firms, are generally less likely to have exhibited high growth during the years 2006-2010. The notable exception to this is how mature firms with exceptionally high growth during the years 2004-2006 have a probability of high growth also in 2006-2010 that is not significantly different from that of new firms.

From the perspective of resource-based theories, the most noticeable pattern is found in between the two extremes (EXPOST > 2). For one, firms that experienced negative growth during the years 2004-2006, and thus weakened their resource positions accordingly, are significantly less likely to exhibit positive growth in the years 2006-2010 than are new firms, irrespective of innovation output. These firms were also found less likely to innovate. Firms that exhibited positive growth during the years 2004-2006 are more likely to exhibit positive growth also in the four-year period that follows, irrespective of innovation output: Supplementary pairwise comparisons find all of the coefficients indicating negative growth (EXANTE_1 and EXANTE_2) to be significantly different from the coefficients that indicate positive growth (EXANTE_3, EXANTE_4 and EXANTE_5), at the 5 per cent level or stronger[6]. This expresses the cumulative, self-reinforcing effects that resource-based theories suggest are at play between resource-accumulation through initial growth, development work that build on these resources and strengthen market and resource positions, and further growth in employment.

4.4. Multicollinearity, interaction effects and alternative estimation strategies

Models 3 through 6 regresses growth on variables that in Table 2 (descriptive statistics and bivariate correlations) and Table 3 (multivariate probit estimations of innovation output) are shown to be correlated. This raises questions concerning potential multicollinearity biases. Supplementary tests for multicollinearity between the exogenous variables of Model 3 to Model 6 yield a moderate mean variance inflation factor of 1.68, and a condition number of 13.147. The latter is well below the rule-of-thumb thresholds of 15 for moderate multicolinearity and 30 for serious multicolinearity (Carlsson & Lundström, 2002; Maddala, 1992; Varga, 2000).

Quantile regressions on a continuous growth measure may seem more appropriate than the ordered logit estimator when the effects of the independent variables, contrary to the basic assumptions of the ordered logit, are expected to vary between different levels of the dependent variable (Alex Coad & Rao, 2008; Ebersberger & Herstad, 2013; Ebersberger, Marsili, Reichstein, & Salter, 2010; García-Manjón & Romero-Merino, 2012; Reichstein et al., 2010). As stated above, one of the reasons for the choice of a categorical ordered

---

[6] Walds Chi2 test statistics for 2 (variables indicating negative growth) x 3 (variables indicating positive growth) = 6 pairwise comparisons are not reported in detail but available from the authors upon request.

dependent variable is that it allows us to treat survival as part of the growth construct. Quantile regressions, on the other hand, open up sample selection issues (Heckman, 1979; Nawata, 1994) because they can only be estimated for the subsample of firms that survived from 2008 (CIS sampling) to 2010 (end year the computation of growth).

To investigate whether our results are sensitive to the choices made, we have run quantile regressions (quantiles .1, .25, .50, .75 and .90, in accordance with e.g. García-Manjón & Romero-Merino, 2012) on the actual growth rate, for survivor firms only. This has been done with and without the inclusion of Mills ratio as a control for sample selection (Greene, 2000). This ratio was manually computed based on a probit model that estimated the probability of survival (eg. Ebersberger & Herstad, 2012), and thus mirrored the reported logit Model 3[7]. Without the control for sample selection, the quantile regression yields results that in substantive terms are consistent with those obtained from the ordered logit with Brant's test, and then from the binary logits. With the Mills ratio included, the results remain structurally consistent at considerably weaker levels of significance. A condition number as high as 89.303 for the model with sample selection control indicates that it suffers from high standard errors due to severe multicollinearity in the absence of robust exclusion restriction (Bushway, Johnson, & Slocum, 2007; Puhani, 2000), i.e. a variable that explains survival but does not correlate with actual growth. Therefore, we believe this estimation strategy raises more issues than it resolves. Last, we have also estimated Tobit regressions wherein survival is treated as a question of censoring (cf. Laursen & Salter, 2006). The baseline results obtained are consistent with those reported from the ordered logit Model 3, yet, the Tobit estimator cannot reveal the conditional nature of the relationships between innovation and growth. Therefore, it is inappropriate.

A last issue concerns complementarities between technical inventive capacity, signaled by patent applications, and commercial innovation capacity, signaled by the composition of innovation output. In our empirical approach, this translates into a question of interaction effects between PROPAT on the one hand, and PROD_ONLY, PROC_ONLY and BOTH on the other. When the three two-way interaction terms are included in Model 3, they are found insignificant and the overall explanatory power of the model remains more or less the same[8].

---

[7] The results of the sample selection stage (EXPOST > 0) and quantile outcome regressions with and without sample selection controls are available from the authors upon request.
[8] Pseudo R2 increases from 0.0333 in the reported Model 3, to 0.0334 in the alternative Model 3 that include interaction terms

5. Implications

The conditional nature of the relationships between R&D intensity, patent output and growth found in several prior studies (e.g Alex Coad & Rao, 2008) mirror those of studies that more generally have found of firm-specific characteristics to influence growth differently depending on what parts of the distribution that is considered (Reichstein et al., 2010). These are important contributions, because they show that events that span from severe downsizing or through moderate upscaling and into very high growth are unique in their own right and may be triggered, moderated or reinforced differently by various firm-specific characteristics, strategies and output. However, our findings suggest that this must not be allowed to overshadow how other, and more fundamental aspects of firms as knowledge-generating and processing organizations, are consistent determinants of employment performance because they are empirical expressions of the larger, underlying capacity construct upon which this performance generally depends.

This is evident from the positive estimates obtained for combined product and process innovation on all levels of employment growth considered herein; compared to the conditional impacts that are detected also by us analysis: The role of product innovation per se in supporting survival point to the importance of new products in defining market niches and in positioning the firm *for* growth, which materializes when paralleled by the process innovation that signal willingness to invest in complementary production processes and support functions. Process innovations, as broadly defined and operationalized herein, are in turn not only linked to strong growth in the past. They are also vital in laying the foundation for employment growth in the future, either in themselves, and if so only conditionally; or unconditionally when they are part of multi-faceted innovation strategies whereby firms also introduce new products to defend their market positions, carve out new market niches or explore their current capabilities in new commercial domains.

In this way, improvements in the 'way things are done' in the internal organization emerge from our analysis as integral to the larger capability construct. Compared to the focus in antecedent literature on R&D, patents and product innovations per se, and contrary to what is often assumed based on this work, this means that a stronger analytical focus on the internal resources and processes of firms are needed in order for the dynamics of innovation-based employment growth to be understood.

6. Conclusion and limitations

This paper has used resource-based theories of the firm as the point of departure for understanding the complex interplay between organizational resources and capabilities, innovation output and employment growth. Our findings are consistent with the notion that self-reinforcing effects are at play in determining positive as well as and negative growth trajectories: Firms that exhibit positive growth and in this way signal strong resource positions tend to exploit these resources through development work that materialize as bundles of complementary innovations, which further strengthen their market power, employment performance, and thus resource positions and capabilities. Conversely, weak growth is not only autocorrelated but self-reinforcing, as ex ante decreases in employment reduces the probability that innovations are introduced that contribute to unlocking the negative employment performance path that has been initiated.

It must be noted that three factors, that are themselves related to the capabilities construct, reduces the degree of employment concentration implied in this line of argumentation. A first set of limitations to growth operate at the level the firm itself. Capabilities in general and innovation capacity in particular, arises not from the control over resources per se, but from the ability to coordinate and integrate these resources into productive work. The resulting dependence of growth-inducing capabilities on strategic management control and knowledge integration routines limit the scale and scope of corporate activity. Moreover, capabilities may turn into rigidities when circumstances change beyond firms' abilities to adjust products, processes and business models, and put previously strong employment performers onto negative, self-reinforcing growth paths (Leonard-Barton, 1992). In dynamic technological and market environment, the line that distinguishes valuable core capabilities from harmful rigidities may be very thin.

A second set of limitations operates at the level of industries and territorial economies. Knowledge spillovers entail that firms cannot fully internalize the learning effects of their development work and business activities more generally (Arrow, 1962). It is plausible that the more valuable the resources of firms currently are, the more their employees will be in demand by other firms with weaker resource positions (Combes & Duranton, 2006; Pesola, 2011). Strong resource positions also increase the likelihood that employees leave in groups and establish spin-offs that not only build on the resources of the former employer firm, but also replicate some of its capabilities (Andersson & Klepper, 2013). Moreover, some of the growth impetuous experienced when the resources and capabilities of a firm are in demand will inevitably spill over on its value chain partners.

Third, the systems of corporate governance that have evolved in many Western economies since the crisis of the 1970s (Herstad, 2011; M. C. Jensen, 1993; Pedersen & Thomsen, 1999) tend to constrain corporate activity beyond the levels of scale and scope that outside investors are able to evaluate and appreciate based on publicly available information on the firm (Fuller & Jensen, 2002; Herstad, 2005; Lazonick, 2006) . If firms, from their own endogenous dynamics, grow beyond these levels, the financial markets may respond by forcing them to 'downsize and distribute' their activities and resource bases (Froud, Sukhdev, Leaver, & Williams, 2006; Lazonick & O'Sullivan, 2000).

As any empirical study, ours has notable limitations. The data does not allow us to observe innovation activity and output prior to the CIS2008 reference period, and our approach rely solely on the controls for ex ante growth to capture remaining *direct* effects of this on growth ex post. Moreover, innovation output is observed in the three-year period that follows *after* the start of the five-year period for which growth is computed. Some simultaneity is therefore present in the estimations, and means that we cannot determine with certainty whether employment growth occurs prior to the introduction of innovations, as a part of the development work; or follow in the wake of it. Still, we have determined that the effects endure for a minimum of two years ex post.

Furthermore, we believe the substantive implications of these empirical limitations are modest due to our focus on the cumulative interplay between direct and indirect effects of development work on the resource positions and capabilities of firms. Following the theoretical perspective applied, correlations between observed (during the reference period) and unobserved (prior to or after the reference period) innovation output are to be expected due to the underlying, yet unobserved, capabilities that resource-based theories postulate is the ultimate determinant of employment performance. This poses a problem primarily to the extent that one is seeking to isolate the effect of *specific innovations* on employment from the effects of resource-positions and capabilities more generally. We have sought to do the opposite.

Three limitations that are associated with our focus on employment growth at the level of the firm warrant attention. The first is that we have not considered how innovation capacity, output and employment is associated with other performance measures that may be higher on the agenda of managers and investors, such as productivity and profitability. Thus, we cannot determine whether there are trade-offs between the organizational structures and complex, multi-faceted innovation strategies that our analysis suggest form the basis for long-term employment performances; and those that are preferable from the perspective of more

immediate financial returns– and therefore may weigh heavier in corporate decision making (M. C. Jensen & Meckling, 1976; Lazonick & O'Sullivan, 2000). Increased insight into how the management preferences and governance structures that characterizes contemporary capitalism, notably the separation of equity ownership and management control (Lazonick, 2007; Lazonick & O'Sullivan, 2000), influences business strategies, development work and thus the number and quality of jobs provided by firms (Bassanini & Ernst, 2002; Kleinknecht, van Schaik, & Zhou, 2014; Zhou, Dekker, & Kleinknecht, 2011) are therefore of vital importance to the formulation of industrial policy.

Second, studies of growth at the level of individual firms cannot, due to business stealing effects, determine the net effects of innovation on employment at the level of the economy (Mastrostefano & Pianta, 2009). Still, the reallocation of labor between innovative and non-innovative firms that this type of analysis may be biased by is also an essential aspect of the larger evolutionary processes that contribute either to the reproduction of current industrial specializations, or to structural change. Third, our analysis does not capture the external employment effects of the focal firms' development work. A substantial proportion of these effects may materialize amongst value chain partners, or amongst other organizations that strengthen their own resource positions and capabilities by tapping into the labor market spillovers generated by the focal firm.

Compared to the problem of business stealing effects, this points to the diametrically opposing risk that we have underestimated rather than overestimated the importance of complex, multi-faceted development work to the dynamics of the economy as a whole. This serves to underscore our main conclusion: That employment performance is intimately interlinked with the accumulation and exploitation of organizational resources and capabilities that extend well beyond the realms of technical inventive activity and new product introductions per se.

References

Aglietta, M., & Breton, R. (2001). Financial systems, corporate control and capital accumulation. *Economy and Society, 30*(4), 433-466.

Andersson, M., & Klepper, S. (2013). Characteristics and performance of new firms and spinoffs in Sweden. *Industrial and Corporate Change, 22*(1), 245-280. doi: 10.1093/icc/dts046

Arrow, K. J. (1962). The Economic Implications of Learning by Doing. *The Review of Economic Studies Ltd., 29*(3), 155-173.

Arundel, A., & Kabla, I. (1998). What percentage of innovations are patented? empirical estimates for European firms. *Research Policy, 27*(2), 127-141. doi: 10.1016/S0048-7333(98)00033-X

Balsvik, R. (2011). Is labor mobility a channel for spillovers from multinationals? Evidence from Norwegian manufacturing. *Review of Economics and Statistics, 93*(1), 285-297.

Barbero, J. L., Casillas, J. C., & Feldman, H. D. (2011). Managerial capabilities and path to growth as determinants of high-growth small and medium-sized enterprises. *International Small Business Journal, 29*(6), 671-694.

Bassanini, A., & Ernst, E. (2002). Labour market regulation, industrial relations and technological regimes: a tale of comparative advantage. *Industrial and Corporate Change, 11*(3), 391-426. doi: 10.1093/icc/11.3.391

Beck, T., & Levine, R. (2002). Industry growth and capital allocation: Does having a market- or bank-based system matter? *Journal of Financial Economics, 64*, 147-180.

Beck, T., Levine, R., & Loayza, N. (2000). Finance and the Sources of Growth. *Journal of Financial Economics, 58*, 261-300.

Bottazzi, L., & Peri, G. (1999). *Innovation, Demand and Knowledge Spillovers: theory and evidence from European regions*. London: Centre for Economic Policy Research.

Brant, R. (1990). Assessing Proportionality in the Proportional Odds Model for Ordinal Logistic Regression. *Biometrics, 46*(4), 1171-1178.

Breschi, S., & Lenzi, C. (2010). Spatial patterns of inventors' mobility: Evidence on US urban areas. *Papers in Regional Science, 89*(2), 235-250. doi: 10.1111/j.1435-5957.2010.00300.x

Bushway, S., Johnson, B. D., & Slocum, L. A. (2007). Is the magic still there? The use of the Heckman two-step correction for selection bias in criminology. *Journal of Quantiative Criminology, 23*(2), 151-178.

Cappellari, L., & Jenkins, S. P. (2003). Multivariate probit regressions using simulated maximum likelihood. *The Stata Journal, 3*(3), 278-294.

Carlsson, F., & Lundström, S. (2002). Economic Freedom and Growth: Decomposing the Effects. *Public Choice, 112*(3-4), 335-344. doi: 10.1023/A:1019968525415

Carpenter, M., Lazonick, W., & O'Sullivan, M. (2003). The stock market and innovative capabilities in the New Economy: The optical networking industry. *Industrial and Corporate Change, 12*(5), 963-1034.

Cassiman, B., & Veugelers, R. (2006). In search of complementarity in innovation strategy: Internal R&D and external knowledge aquisition. *Management Science, 52*(1), 68-82.

Cefis, E., & Orsenigo, L. (2001). The persistence of innovative activities - A cross-countries and cross-sectors comparative analysis. *Research Policy, 30*(7), 1139-1158. doi: 10.1016/s0048-7333(00)00139-6

Chib, S., & Greenberg, E. (1998). Analysis of multivariate probit models. *Biometrika, 85*(2), 347-361.

Coad, A. (2006). A closer look at serial growth rate correlations. *Working papers, Laboratory of Economics and Management, 2006*(29).

Coad, A., & Rao, R. (2008). Innovation and firm growth in high-tech sectors: A quantile regression approach. *Research Policy, 37*(4), 633-648. doi: http://dx.doi.org/10.1016/j.respol.2008.01.003

Cody, R. P., & Smith, J. K. (1991). *Applied statistics and the SAS programming language*. New Jersey: Prentice Hall

Combes, P. P., & Duranton, G. (2006). Labour pooling, labour poaching, and spatial clustering. *Regional Science and Urban Economics, 36*(1), 1-28. doi: 10.1016/j.regsciurbeco.2005.06.003

Del Monte, A., & Papagni, E. (2003). R&D and the growth of firms: empirical analysis of a panel of Italian firms. *Research Policy, 32*(6), 1003-1014. doi: http://dx.doi.org/10.1016/S0048-7333(02)00107-5

Demirel, P., & Mazzucato, M. (2014). Innovation and Firm Growth: Is R&D Worth It? *Industry and Innovation, 19*(1), 45-62. doi: 10.1080/13662716.2012.649057

Dokko, G., Wilk, S. L., & Rothbard, N. P. (2009). Unpacking Prior Experience: How Career History Affects Job Performance. *Organization Science, 20*(1), 51-68. doi: 10.1287/orsc.1080.0357

Dougherty, D. (1992). A practice-centered modell of organizational renewal through product innovation. *Strategic Management Journal, 13*, 77-92.

Dunne, P., & Hughes, A. (1994). Age, Size, Growth and Survival: UK Companies in the 1980s. *The Journal of Industrial Economics, 42*(2), 115-140. doi: 10.2307/2950485

Ebersberger, B., & Herstad, S. (2011). Product innovation and the complementarities of external interfaces. *European Management Review, 8*(3), 117-135.

Ebersberger, B., & Herstad, S. (2012). Go abroad or have strangers visit? On organizational search spaces and local linkages *Journal or Economic Geography, 12*(1), 273-295.

Ebersberger, B., & Herstad, S. (2013). The relationship between international innovation collaboration, intramural R&D and SME's innovation performance: A quantile regression approach. *Applied Economic Letters, 20*(7), 626-630.

Ebersberger, B., Marsili, O., Reichstein, T., & Salter, A. (2010). Into thin air - using a quantile regression approach to explore the relationship between R&D and innovation. *Journal of Applied Economics, 24*(1), 95-102.

Eriksson, R. H. (2011). Localized Spillovers and Knowledge Flows: How Does Proximity Influence the Performance of Plants? *Economic Geography, 87*(2), 127-152. doi: 10.1111/j.1944-8287.2011.01112.x

Evangelista, R., & Vezzani, A. (2010). The economic impact of technological and organizational innovations. A firm-level analysis. *Research Policy, 39*, 1253-1263.

Evans, D. (1987). The relationship between firm growth, size and age: estimates for 100 manufacturing industries. *The Journal of Industrial Economics, XXXV*(4), 567-581.

Fogliatto, F. S., da Silveira, G. J. C., & Borenstein, D. (2012). The mass customization decade: An updated review of the literature. *International Journal of Production Economics, 138*(1), 14-25. doi: http://dx.doi.org/10.1016/j.ijpe.2012.03.002

Foss, N. J., Lygsie, J., & Zahra, S. A. (2013). The role of external knowledge sources and organizational design in the process of opportunity exploitation. *Strategic Management Journal, 34*, 1453-1471.

Freel, M., & Robson, P. J. A. (2004). Small firm innovation, growth and performance: Evidence from Scotland and Northern England. *International Small Business Journal, 22*(6), 561-575.

Froud, J., Sukhdev, J., Leaver, A., & Williams, K. (2006). *Financialization and strategy*. New York: Routledge.

Fuller, J., & Jensen, M. C. (2002). Just say no to Wall Street. *Journal of Applied Corporate Finance, 14*(4), 41-46.

Gambardella, A., Giuri, P., & Luzzi, A. (2007). The market for patents in Europe. *Research Policy, 36*(8), 1163-1183. doi: 10.1016/j.respol.2007.07.006

García-Manjón, J. V., & Romero-Merino, M. E. (2012). Research, development, and firm growth. Empirical evidence from European top R&D spending firms. *Research Policy, 41*(6), 1084-1092. doi: http://dx.doi.org/10.1016/j.respol.2012.03.017

Geroski, P., Machin, S., & Reenen, J. V. (1993). The Profitability of Innovating Firms. *The RAND Journal of Economics, 24*(2), 198-211. doi: 10.2307/2555757

Gibrat, R. (1931). *Les inégalitiés economiques*. Paris: Requeil Sirey.

Goedhuys, M., & Veugelers, R. (2012). Innovation strategies, process and product innovations and growth: Firm-level evidence from Brazil. *Structural Change and Economic Dynamics, 23*(4), 516-529. doi: http://dx.doi.org/10.1016/j.strueco.2011.01.004

Grant, R. (1996). Prospering in dynamically-competitive environments: organizational capability as knowledge integration. *Organization Science, 7*, 375-387.

Greenan, N., & Guellec, D. (2000). Technological innovation and employment reallocation. *Labour, 14*(4), 547-590.

Greene, W. H. (2000). *Econometric Analysis (4 ed.)*. Upper Saddle River: Prentice Hall.

Grimpe, C., & Kaiser, U. (2010). Balancing Internal and External Knowledge Acquisition: The Gains and Pains from R&D Outsourcing. *Journal of Management Studies, 47*(8), 1483-1509. doi: 10.1111/j.1467-6486.2010.00946.x

Grossman, G. M., & Helpman, E. (1991). Quality ladders in the theory of growth. *Review of Economic Studies, 58*(1), 43-61.

Hall, B. H., Lotti, F., & Mairesse, J. (2008). Employment, innovation, and productivity: evidence from Italian microdata. *Industrial and Corporate Change, 17*(4), 813-839. doi: 10.1093/icc/dtn022

Harrison, R., Jaumandreu, J., Mairesse, J., & Peters, B. (2008). Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European Countries. *NBER Working Paper 14216*.

Hauknes, J., & Knell, M. (2009). Embodied knowledge and sectoral linkages: An input-output approach to the interaction of high- and low-tech industries. *Research Policy, 38*(3), 459-469.

Heckman, J. J. (1979). Sample selection bias as a specifcation error. *Econometrica, 47*(1), 153-161.

Herstad, S. (2005). *Utenlandsk direkte eierskap (Foreign Direct Ownership)*. Oslo: University of Oslo.

Herstad, S. (2011). Paradigms, Regimes and the Shifting Notions of Institutional Best Practice. *Journal of the Knowledge Economy, 2*(2), 173-191. doi: 10.1007/s13132-010-0030-7

Herstad, S., Aslesen, H. W., & Ebersberger, B. (2014). On industrial knowledge bases, commercial opportunities and global innovation network linkages. *Research Policy, 43*(3), 495– 504. doi: 10.1016/j.respol.2013.08.003

Herstad, S., & Brekke, T. (2012). Globalization, modes of innovation and regional knowledge diffusion infrastructures. *European Planning Studies, 20*(10), 603-1625.

Herstad, S., & Sandven, T. (2014a). Marked for life? On researcher involvement at infancy and the innovative capabilities of survivor firms. *Applied Economics Letters (forthcoming), 21*(17), 1210-1213. doi: DOI:10.1080/13504851.2014.920464

Herstad, S., & Sandven, T. (2014b). When are recruited competences supportive of innovation? Inter-industry differences in the importance of diversity and similarity. *Paper under review*.

Herstad, S., Sandven, T., & Ebersberger, B. (2015). Recruitment, knowledge integration and modes of innovation. *Research Policy, 44*(1), 138-153. doi: http://dx.doi.org/10.1016/j.respol.2014.06.007

Herstad, S., Sandven, T., & Solberg, E. (2013). Location, education and enterprise growth. *Applied Economics Letters, 20*(10), 1019-1022.

Hoopes, D. G., & Postrel, S. (1999). Shared knowledge, "glitches," and product development performance. *Strategic Management Journal, 20*(9), 837-865.

Jensen, M. B., Johnson, B., Lorenz, E., & Lundvall, B. A. (2007). Forms of knowledge and modes of innovation. *Research Policy, 36*, 680-693.

Jensen, M. C. (1993). The modern industrial revolution, exit and the failure of internal control systems. *Journal of Finance*(July 1993), 831-880.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics, 3*
(4), 305-360.

Kleinknecht, A., van Schaik, F. N., & Zhou, H. (2014). Is flexible labour good for innovation? Evidence from firm-level data. *Cambridge Journal of Economics*. doi: 10.1093/cje/bet077

Kogut, B., & Zander, U. (1992). Knowledge of the firm, cominative capabilities and the replication of technology. *Organization Science, 3*(3), 383-397.

Laursen, K., & Salter, A. (2006). Open for innovation: The role of openness in explaining innovation performance among UK manufacturing firms. *Strategic Management Journal, 27 (2)* 131-150.

Lazonick, W. (2006). Evolution of the New Economy Business Model. *Business and Economic History Online*.

Lazonick, W. (2007). The US stock market and the governance of innovative enterprise. *Industrial and Corporate Change, 16*(6), 983-1035.

Lazonick, W., & O'Sullivan, M. (2000). Maximizing shareholder value: A new ideology for corporate governance. *Economy and Society, 29*(1), 13-35.

Lee, C.-Y. (2010). A theory of firm growth: Learning capability, knowledge threshold, and patterns of growth. *Research Policy, 39*(2), 278-289. doi: http://dx.doi.org/10.1016/j.respol.2009.12.008

Leonard-Barton, D. (1992). Core capabilities and core rigidities: A paradox in new product development. *Strategic Management Journal, 13*, 111-125.

Long, J. S., & Freese, J. (2006). *Regression models for categorical dependent variables using Stata* (2 ed.). College Station, TX: Stata Press.

Macher, J. T., & Mowery, D. C. (2009). Measuring dynamic capabilities: Practies and performance in semiconductor manufacturing. *British Journal of Management, 20*(S1), 41-62.

Maddala, G. S. (1992). *Introduction to Econometrics*. London & New York: Prentice Hall.

Mansury, M. A., & Love, J. H. (2008). Innovation, productivity and growth in US business services: A firm-level analysis. *Technovation, 28*(1–2), 52-62. doi: http://dx.doi.org/10.1016/j.technovation.2007.06.002

Mastrostefano, V., & Pianta, M. (2009). Technology and jobs. *Economics of Innovation and New Technology, 18*(8), 729-741. doi: 10.1080/10438590802469552

Nawata, K. (1994). Estimation of sample selection bias models by the maximum likelihood estimator and Heckman's two-step estimator. *Economic Letters, 45*, 33-40.

Nightingale, P., & Coad, A. (2014). Muppets and gazelles: political and methodological biases in entrepreneurship research. *Industrial and Corporate Change, 23*(1), 113-143. doi: 10.1093/icc/dtt057

Ocasio, W. (1997). Towards an attention-based view of the firm. *Strategic Management Journal, 18*, 187-206.

Pedersen, T., & Thomsen, S. (1999). Economic and systemic explanations of ownership concentration among Europe's largest companies. *International Journal of the Economics of Business, 6*(3), 367-381.

Penrose, J. (1959). *The theory of the growth of the firm*. New York: John Wiley and Sons.

Pesola, H. (2011). Labour Mobility and Returns to Experience in Foreign Firms. *The Scandinavian Journal of Economics, 113*(3), 637-664. doi: 10.1111/j.1467-9442.2011.01649.x

Piening, E. P., & Salge, T. O. (2014). Understanding the Antecedents, Contingencies, and Performance Implications of Process Innovation: A Dynamic Capabilities Perspective. *Journal of Product Innovation Management*, n/a-n/a. doi: 10.1111/jpim.12225

Pine, J. (1993). *Mass customization: The frontier in business research*: Harvard Business Press

Puhani, P. A. (2000). The Heckman correction for sample selection and its critique. *Journal of Economic Surveys, 14*(1), 53-68.

Reichstein, T., Dahl, M. S., Ebersberger, B., & Jensen, M. B. (2010). The devil dwells in the tails. *Journal of Evolutionary Economics, 20*(2), 219-231. doi: 10.1007/s00191-009-0152-x

Reichstein, T., & Jensen, M. B. (2005). Firm size and firm growth rate distributions—The case of Denmark. *Industrial and Corporate Change, 14*(6), 1145-1166. doi: 10.1093/icc/dth089

Roper, S., Du, J., & Love, J. H. (2008). Modelling the innovation value chain. *Research Policy, 37*(6-7), 961-977. doi: 10.1016/j.respol.2008.04.005

Singh, J., & Agrawal, A. (2011). Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management Science, 57*(1), 129-150.

Smolny, W. (1998). Innovations, Prices and Employment: A Theoretical Model and an Empirical Application for West German Manufacturing Firms. *The Journal of Industrial Economics, 43*(3), 359-381.

Stam, E., & Wennberg, K. (2009). The roles of R&D in new firm growth. *Small Business Economics, 33*(1), 77-89. doi: 10.1007/s11187-009-9183-9

Sutton, J. (1997). Gibrat's Legacy. *Journal of Economic Literature, 35*(1), 40-59. doi: 10.2307/2729692

Teece, D., & Pisano, G. (1994). The Dynamic Capabilities of Firms: an Introduction. *Industrial and Corporate Change, 3*(3), 537-556. doi: 10.1093/icc/3.3.537-a

Teece, D., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(78), 509-533.

Tether, B. S. (2002). Who co-operates for innovation and why? An empirical analysis. . *Research Policy, 31*, 947-967.

Timmermans, B., & Boschma, R. (2014). The effect of intra- and inter-regional labour mobility on plant performance in Denmark: the significance of related labour inflows. *Journal of Economic Geography, 14*(2), 289-311. doi: 10.1093/jeg/lbs059

Varga, A. (2000). Local Academic Knowledge Transfers and the Concentration of Economic Activity. *Journal of Regional Science, 40*(2), 289-309. doi: 10.1111/0022-4146.00175

Wang, H. C., He, J. Y., & Mahoney, J. T. (2009). Firm-specific knowledge resources and competitive advantage: The roles of economic and relationship-based employee governance mechanisms. *Strategic Management Journal, 30*(12), 1265-1285. doi: 10.1002/smj.787

Wernerfelt, B. (1984). A Resource-Based View of the Firm. *Strategic Management Journal, 5*(2), 171-180.

Williams, R. (2006). Generalized ordered logit/partial proportional odds models for ordinal dependent variables. *The Stata Journal, 6*(1), 58–82.

Zahra, S. A., & Nielsen, A. P. (2002). Sources of capabilities, integration and technology commercialisation. *Strategic Management Journal, 23*, 377-398.

Zhong, R. Y., Dai, Q. Y., Qu, T., Hu, G. J., & Huang, G. Q. (2013). RFID-enabled real-time manufacturing execution system for mass-customization production. *Robotics and Computer-Integrated Manufacturing, 29*(2), 283-292. doi: http://dx.doi.org/10.1016/j.rcim.2012.08.001

Zhou, H., Dekker, R., & Kleinknecht, A. (2011). Flexible labor and innovation performance: evidence from longitudinal firm-level data. *Industrial and Corporate Change, 20*(3), 941-968. doi: 10.1093/icc/dtr013

Tables

Table 1: Sample distribution on ex post growth categories

	Distribution		Growth rate	
EXPOST	*Observations*	*Percentage*	*Min*	*Max*
0	253	5,50	-	-
1	807	17,53	-4,412	-0,182
2	906	19,68	-0,183	0
3	887	19,27	0,004	0,182
4	886	19,24	0,183	0,430
5	865	18,79	0,431	7,240
N	4604	100		

Note. Growth rate = Log (employment in 2010) – log (employment in 2006) = log (employment in 2010/employment in 2006).

Table 2: Descriptive statistics and bivariate correlations

		Mean	SD	Max	1	2	3	4	5	6	7	8
1	EXPOST	2,856	1,521	5	1							
2	PROD_ONLY	0,124	0,329	1	0,002	1						
3	PROC_ONLY	0,073	0,260	1	0,001	-0105***	1					
4	BOTH	0,133	0,339	1	0,041***	-0,147***	-0,109***	1				
5	PROPAT	0,100	0,300	1	0,019	0,225***	-0,018	0,222***	1			
6	SIZE_04	3,338	1,534	9,924	-0,186***	0,008	0,042***	0,074***	0,087***	1		
7	SIZE_06	3,693	1,210	9,885	-0,195***	0,022	0,052***	0,078***	0,118***	0,760***	1	
8	HIGHED	0,073	0,139	1	0,115***	0,119***	-0,013	0,120***	0,182	-0,100***	-0,073***	1
9	EXANTE_NEW	0,084	0,278	1	0,080***	0,007	-0,013	-0,038***	0,001	-0,661***	-0,159***	0,087***
10	EXANTE_1	0,171	0,376	1	-0,068***	-0,025	-0,019	-0,016	-0,003**	0,167***	-0,036***	-0,068***
11	EXANTE_2	0,177	0,382	1	-0,083***	-0,018	-0,003	-0,025*	-0,029	0,175***	0,062***	-0,052***
12	EXANTE_3	0,206	0,405	1	-0,030***	0,003***	0,047***	0,016	0,007	0,206***	0,132***	-0,038**
13	EXANTE_4_	0,184	0,388	1	0,009	-0,001	-0,002	0,026*	-0,011	0,061***	0,006***	0,044***
14	EXANTE_5	0,178	0,382	1	0,113***	0,036	-0,017	0,026*	0,035***	-0,137	-0,056***	0,052***

Note: The minimum value for all variables is zero. Bivariate correlations between mutually exclusive past growth categories are not reported.

***, ** and * indicate significance at 1 per cent, 5 per cent and 10 per cent levels respectively.

N = 4604.

Table 3: Innovation output regressed on ex ante growth levels.

	Model 1					
	Equation A PRODUCT = 1		Equation B PROCESS = 1		Equation C PROPAT = 1	
	Coeff	*SE*	*Coeff*	*SE*	*Coeff*	*SE*
SIZE_06	0,136	0,019***	0,131	0,019***	0,229	0,024***
HIGHED	1,637	0,175***	0,799	0,179***	1,930	0,201***
EXANTE_NEW	*Reference*		*Reference*		*Reference*	
EXANTE_1	-0,504	0,122***	-0,416	0,123***	-0,838	0,154***
EXANTE_2	-0,477	0,122***	-0,376	0,123***	-0,974	0,156***
EXANTE_3	-0,293	0,118**	-0,146	0,120	-0,808	0,150***
EXANTE_4_	-0,316	0,115***	-0,195	0,116*	-0,854	0,145***
EXANTE_5	-0,118	0,107	-0,159	0,110	-0,493	0,134***

Note: Coefficient estimates and standard errors from multivariate probit regression estimated with 50 draws.
***, ** and * indicate significance at 1 per cent, 5 per cent and 10 per cent levels respectively.
14 sector dummies are included that are jointly significant in all three equations.
N = 4604. Wald Chi2 (63)   =   997.57***.

Table 4: Baseline regressions and Brant's test

| | Dependent variable: EXPOST | | | | Brant's test of parallel regression lines | | | | | |
| | Model 2 | | Model 3 | | Estimated coefficients from binary regressions EXPOST > X | | | | | Chi2 |
	Coeff	SE	Coeff	SE	> 0	> 1	> 2	> 3	> 4	
PROD_ONLY	0,216	0,086**	0,148	0,087*	0,793	0,221	0,143	0,130	-0,025	8,380*
PROC_ONLY	0,173	0,104*	0,159	0,104	0,105	0,073	0,077	0,123	0,472	8,770*
BOTH	0,455	0,085***	0,407	0,085***	0,432	0,405	0,430	0,346	0,359	1,000
PROPAT	0,217	0,097**	0,166	0,097*	0,042	0,134	0,059	0,139	0,312	3,370
SIZE_06	-0,348	0,023***	-0,324	0,024***	0,037	-0,168	-0,227	-0,408	-0,642	146,270***
HIGHED			0,960	0,251***	0,052	0,591	0,975	0,823	0,858	4,310
EXANTE_NEW			*Reference*							
EXANTE_1			-0,616	0,118***	0,425	-0,087	-0,464	-0,678	-0,618	27,180***
EXANTE_2			-0,607	0,117***	0,363	0,101	-0,356	-0,880	-1,082	57,650***
EXANTE_3			-0,406	0,115***	0,624	0,434	-0,107	-0,565	-0,937	66,340***
EXANTE_4_			-0,369	0,116***	0,463	0,308	-0,109	-0,399	-0,643	35,260***
EXANTE_5			0,039	0,119	0,389	0,261	0,144	0,035	0,137	4,000
N	4604		4604							
LR Chi2 (df)	436.91 (19)***		531.23 (25)***							
Pseudo R2	0.027		0.033							

Note: Coefficient estimates and standard errors from ordered logistic regressions.
***, ** and * indicate significance at 1 per cent, 5 per cent and 10 per cent levels respectively.
All regressions include 14 jointly significant sector dummies.

Note: Coefficients from j – 1 binary regressions. Significant Chi2 test statistics indicate that the parallel regression line assumption is violated

Table 5: Binary logistic regressions on ex post growth thresholds.

	Model 4 EXPOST > 0		Model 5 EXPOST > 2		Model 6 EXPOST > 4		Coefficient differences Walds Chi2	
	Coeff	*SE*	*Coeff*	*SE*	*Coeff*	*SE*	*Model 4 compared to Model 5*	*Model 5 compared to Model 6*
PROD_ONLY	0,793	0,265***	0,143	0,103	-0,025	0,141	6,04**	1,47
PROC_ONLY	0,105	0,252	0,077	0,121	0,472	0,156***	0,01	6,65***
BOTH	0,432	0,225*	0,430	0,102***	0,359	0,129***	0,00	0,03
PROPAT	0,042	0,262	0,059	0,115	0,312	0,149**	0,00	3,01*
SIZE_06	0,037	0,057	-0,227	0,027***	-0,642	0,042***	20,17***	85,65***
HIGHED	0,052	0,550	0,975	0,303***	0,858	0,319***	3,26*	0,14
EXANTE_NEW	*Reference*		*Reference*		*Reference*			
EXANTE_1	0,425	0,247*	-0,464	0,134***	-0,618	0,157***	14,71***	1,05
EXANTE_2	0,363	0,248	-0,356	0,135***	-1,082	0,169***	9,81***	19,52***
EXANTE_3	0,624	0,253*	-0,107	0,132	-0,937	0,163***	9,43***	26,22***
EXANTE_4	0,463	0,246*	-0,109	0,134	-0,643	0,155***	6,15**	12,24***
EXANTE_5	0,389	0,242	0,144	0,135	0,137	0,144	1,18	0,00
N	4604		4604		4604			
LR Chi2 (df)	47,76 (25)***		327,65 (25) ***		639,65 (25) ***			
Pseudo R2	0,024		0,052		0,144			

Note: Coefficient estimates and standard errors from logistic regressions. ***, ** and * indicate significance at 1 per cent, 5 per cent and 10 per cent levels respectively.
All regressions include 14 jointly significant sector dummies.