Innovation and Productivity
A Microdata Analysis

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This doctoral thesis, with the approval of KTH in Stockholm, will be presented to public examination for the degree of Doctor of Philosophy, on Friday, 27th of March, at 10:00 in Room F3, KTH, Lindstedtsvägen 26, Stockholm.

Printed in Sweden, Universitetsservice US-AB
Abstract

This doctoral thesis consists of four papers. The first two papers deal with firms’ innovation strategies, knowledge spillover and their impact on growth and productivity. The last two papers are focused on spinoffs and their survival.

The first paper finds a strong indication of variation in the capacity of firms to benefit from external knowledge among persistent innovators, temporary innovators and non-innovators. It considers the distinct and complementary effect of internal innovation efforts and spillovers from the local milieu.

The second paper shows that persistently innovative exporters benefit considerably more than other exporters from access to a rich spectrum of neighbouring knowledge. The level of productivity among non-innovative exporters and exporters that are only temporarily engaged in innovation is positively influenced by externalities in the most knowledge-intense local milieus.

The third paper reveals that there is a substantial difference in ex-post entry performance between genuinely new ventures and spinoffs in the manufacturing and service sectors based on their location. The proposed superiority of start-ups by ex-employees depends on the performance measures and the sector. Moreover, knowledge and the technology intensity of the industry matter for the viability of the new firms.

The fourth paper focuses on exports, innovation, tenure and management and investigates how the incumbent firm characteristics affect the viability of its spinoffs. While experience from an exporting parent has a significant and positive effect on market success, no spillover effect from innovative firms can be found.

Keywords
Innovation, Export, knowledge spillover, Location, Productivity Growth, New ventures, Knowledge Acquisition, Spinoff, Survival.

JEL-codes: C23; C25; F21; L25; L26; M13; O31; O32; O47; R11
Acknowledgements

I have received invaluable support during the writing of this thesis. First and foremost, I would like to thank my supervisor Hans Lööf, for giving me the opportunity to work with him, and for his unflagging support and encouragements. His door was always open to me. His kindness, energy, and commitment at work have inspired me and are infinitely admired.

I would like to acknowledge Börje Johansson, my co-author and teacher over the years, for his guidance. Moreover, I want to thank my co-supervisor Kristina Nyström, for her support.

Special thanks to Almas Heshmati who has kindly reviewed my thesis and provided valuable comments.

I am also grateful to all other colleagues at the Division of Entrepreneurship and Innovation, Björn Härsman, Pontus Braunerhjelm, Per Thulin, Anders Broström, Vardan Hovsepyan, Johanna Palmberg, Tomas Sörensson, Gustav Martinsson, Ali Mohammadi, Christian Thomann, and my fellow PhD students Ding Ding, Arvid and Jury for their comments and suggestions in the seminars and also for creating a very pleasant environment at work.

I have been privileged to meet great friends at KTH. To Monia, who is my oldest friend in Sweden; to Zara, who was a great roommate; to Gulzat who made me realize how kind-hearted a person can be, and to Ingrid who was patient with my Swedish, helped me whenever I needed help and taught me a lot of things. It has been great having you around for the daily chats, support at work and to laugh together! Thank you for being such good friends.

It is hard to say how much I am grateful to my mother, Mahrokh and my father Parviz. Their love, encouragement and guidance have been with me all the time. Special thanks to my brother Vahid and my sister Anahid for all their love and support. You all mean a lot to me.

To my beloved husband, Hatef, without his unconditional love, support and wisdom, it would be impossible for me to stand here at the end of this journey. I love you until the end of time!

Stockholm, February 2015

Pardis Nabavi
List of appended papers

This thesis is based on work presented in the following articles.

Paper I


Paper II


Paper III


Paper IV

Nabavi P., Inherited Advantage and Spinoff Success.
Introduction

In contrast to the orthodox neoclassical theory, the Schumpeterian and evolutionary models predict an economy with lasting performance heterogeneity across firms. Empirically, the variability between firms is confirmed in both cross-sectional and time-series measurements. Studying French data, Griliches & Mairesse (1998) find that “something like Mandelbrot’s fractal phenomenon seemed to be at work.” The observed heterogeneity was as different within the total manufacturing as between different bakeries. A similar pattern has been acknowledged for other countries. Exploring the role of micro heterogeneity for aggregate productivity growth in the U.S., Hulten et al. (2001) find significant variation in performance in the same or a narrowly defined sector. Moreover, the heterogeneity tends to be persistent over time.

It has been broadly known that innovation activities are crucial for long-run economic growth and is one major determinant of the performance of firms. This would imply that the observed heterogeneity in performance among firms reflects persistent differences in their innovation activities (Geroski et al. 1997).

Innovation, more than most other economic activities, depends on new knowledge. Although the new knowledge can be acquired through education and experience, it can also be acquired through internal or external knowledge spillovers.

Previous studies have acknowledged that in most fields of innovation and technology, progress is cumulative in that today’s efforts build on prior efforts. Previous experience from associated projects can create internal capabilities within organizations, and learning economies and these categories of internal spillovers tend to moderate the expenditures of new innovation (Nelson & Winter 1982; Attewell 1992; Cohen & Levinthal 1990; Phene & Almeida 2008; Teece 2010). Thus, the persistency in innovation efforts
guarantees the accumulation of internal knowledge; however, disruption can cause the loss and obsolescence of acquired expertise, routines and technology.

In addition, another knowledge spillover mechanism recognized in the literature is entrepreneurship, which is also linked to economic growth (Audretsch and Feldman 2004). However, a new company is not just affected by hereditary knowledge from other companies via entrepreneurial spawning. Experience and knowledge of technical and organizational solutions, markets, and other factors can also spill over from the geographical environment in the form of industrial clusters, agglomerations, labour mobility and proximity to prevailing customers.

In recent years, location and geographical space have received growing attention and shown to be a key component in explaining determinants of innovation and technological change (Audretsch and Feldman 2004). A considerable strand of literature has studied how aggregate knowledge sources inside a region generate spillovers and improve the output of firms located in a region (e.g., Jaffe 1986; Audretsch & Feldman 2004). The classic theories of Marshall (1890) and Jacobs (1969) link agglomerations to the greater development of knowledge due to increased specialization and diversity, respectively. More recent theories of agglomeration (Duranton and Puga 2005) are more specific regarding sharing (indivisible facilities, suppliers, customers, and risk), matching (improved matching of labour or firms, higher probability of matching) and learning (generation, diffusion and accumulation of tacit and codified knowledge).

Although our understanding of how knowledge spillover, agglomeration and innovation work together is widening after the recent theoretical and empirical studies, there is still a lack of deeper understanding of the black box of geographical space, how to measure innovation and who benefits more from knowledge spillover.
The main aim of this dissertation is to assess the effect of innovation and knowledge spillovers and localization on the productivity growth and performance of firms. I exploit the potential in the comprehensive employer-employee data set of Sweden over a long period which is linked to information on innovation and international trade. Multiple indicators of innovation have been used and compared in different papers. The first two papers focus on the innovation strategy of firms, their access to external knowledge potential and the joint effect of these on their productivity growth.

In the last two articles, new ventures and entrepreneurial ventures founded by ex-employees of incumbent firms are in focus. By the systematic study of the properties of both the different categories of spawning companies and the background of the start-up entrepreneurs and by considering their location and knowledge and technology intensity, the aim is to provide new evidence in spinoff literature.

**Methodological approaches**

Aghion & Howitt (2009) argue that the labour productivity measure (which is output per worker) confounds the effect of capital accumulation and technological progress. They show that a better measure of productivity is total factor productivity (TFP), which also tells us how productively the economy uses all the factors of production. Increasing availability of firm-level data allows the estimation of TFP at incumbent establishment level (Bartelsman and Doms 2000). In this thesis, the semi-parametric estimator developed by Levinsohn & Petrin (2003) has been used to estimate TFP. Although some new estimators have been proposed recently, van Beveren's (2012) comparison of the methods shows high correlation and almost identical results regardless of the method used. As a robustness check, the TFP measure is also estimated with Olley & Pakes' (1996) estimation
models. The results show 0.99 correlations with the semi-parametric Levinson-Petrin estimator used in the studies. Moreover, as has been shown by Ackerberg et al. (2007), if labour has a dynamic implication, as is the case for Sweden, models based on the Levinson-Petrin estimator are more suitable, where material is used to invert out productivity.

In the first three papers, the dynamic generalized method of moments (GMM) estimator, which is developed by Arellano & Bover (1995) and Blundell & Bond (1998), is the preferred model. The estimator allows for a dynamic process, in which current realizations of the dependent variable are influenced by former ones, and some regressors may be endogenous. Additionally, the system GMM estimator also accounts for individual specific patterns of heteroskedasticity and serial correlation of the idiosyncratic part of the disturbances.

To analyse the life duration of new firms and spinoffs, in the last two papers, a proportional hazard approach is chosen which allows for discrete time intervals. The model used is a complementary log–log model for panel data which also controls for unobserved individual heterogeneity (Jenkins 2005).

This thesis is based only on a Swedish data set. The advantage of using the Swedish employer-employee data set is its detailed information on individuals, firms, location, trade, and innovation and the coverage of the whole population. Therefore, extensive information for the whole population of firms provides us with the opportunity for systematic studies. Furthermore, for papers III and IV, the comprehensive Swedish employer-employee data set provides the unique possibility to access how the characteristics of the incumbent firm can be transferred to the new firm. Using the same data, Andersson & Klepper (2013) find similar new firm formation patterns for Sweden compared to other advanced countries. Therefore, there is no reason to believe that the findings of these studies would be only valid for the special case of Sweden.
Nonetheless, I am aware of the fact that the empirical findings of this thesis should not be generalized without careful consideration.

**Summary of the results**

Papers I and II address how the productivity growths of firms are affected by internal knowledge generation and knowledge spillovers from neighbouring firms. The first paper considers the Swedish manufacturing and service firms and the second paper includes manufacturing exporters.

We use access to knowledge-intensive producer services as an indicator for the quantity or amount of influential external knowledge in the local milieu.

The results of article I reveal that local milieu and the external knowledge potential have no extra effect on productivity growth of firms with low internal knowledge. The growth rate of total productivity is only weakly linked with external knowledge for firms with occasional innovation efforts. The growth rate of total productivity is strongly associated with external knowledge for firms with persistent innovation efforts. All location types show improvement of internal knowledge. The frequency of patent activity and the self-reported R&D engagement of the firms, both as innovation indicators show robust results.

Recent evidence from the empirical micro-literature suggests that international trade can also have a significant positive impact on innovation and productivity. Therefore, the second paper focuses on the more productive exporting firms in the Swedish manufacturing sector, where the number of new export products of each firm in each year can be identified.

Building on the results of the first article, the second paper investigates whether using different indicators of innovation shows similar results for the more productive exporting firms in Sweden. In this article, constant presence in international markets, frequent engagement in patent application and frequent ability to create
new export products are used as indicators of higher internal knowledge. The results show that firms in knowledge-intensive milieus have a significantly higher level of productivity than firms located in areas with less access to external knowledge. The effect of location is further strengthened by the choice to pursue innovation persistently. No influence of the growth of the external knowledge pool among firms that do not innovate persistently can be found. Nevertheless, a history of prior investment in innovation activities leads to significantly higher growth rates. The cumulative effect of the difference in growth between persistently innovative exporters and other exporters results in greater heterogeneity between the two categories of firms.

Paper III has studied the post-entry evolution of 23,000 new entrants in Sweden throughout the critical first five-year period in the market. We show that manufacturing spinoffs in metro cities are as viable as manufacturing Genuinely New Entrants (GNE) outside metro cites. Moreover, service spinoffs in metro cities have a lower failure risk than GNEs. Considering the value added, no favourable locational conditions can be found among GNEs. In contrast, manufacturing spinoffs in metro cities have significantly higher value added than all other corresponding new starters. No difference in productivity or employment growth can be found among start-ups in manufacturing regarding the origin of the firms (GNEs or spinoffs) or location within industry sectors. Regarding growth in services, we find that entrepreneurial firms in metro cities have significantly higher productivity growth than other entrepreneurs.

Paper IV is a systematic study on both the different characteristics of spawning companies and also the background of the start-up entrepreneurs. The following main results emerge from the last study: (i) spinoffs from exporting firms have a larger market success than other spinoffs, (ii) innovative parents do not produce more viable offspring than other firms, (iii) longer tenure
of founders in the incumbent firms improves the spinoff ability to survive, (iv) accounting for both tenure and managerial experience, the advantage of having an exporting father firm is reduced, while the result is the opposite for ex-employees from innovators. Spinoffs, which are a distinct group of start-ups, can inherit knowledge but it is important to consider what type of knowledge is transferrable and under which conditions this knowledge can be transferred to them.

Concluding remarks
The present thesis is developed based on both theories of agglomeration and endogenous growth. There is a significant similarity between these theories in several respects. The endogenous growth theory assigns a prominent role to concentrations of firms and people for economic development. A basic idea is that spillover and the non-rivalrous nature of knowledge are more beneficial in dense areas (Lucas 1988, Romer 1986). While theories of agglomeration were originally developed to explain the concentration of industries in general, they are also relevant for innovative activity. The classic theories of Marshall (1890) and Jacobs (1969) link agglomerations to the superior development of knowledge due to increased specialization and diversity, respectively. Innovation, more than most other economic activities, depends on new knowledge. More recent theories of innovation and agglomeration are more specific regarding generating, matching, sharing and knowledge diffusion. In many of these theories, the emphasis is commonly on the importance of knowledge accumulation, persistence and absorptive capacity, as well as the multi-person nature of the way organizations innovate. This thesis analyses how firms deal with the challenges addressed in modern theories of economics of agglomeration and economics of innovation and how these challenges have created a substantial heterogeneity in their ability to generate productivity and growth.
The studies presented in this thesis suggest that better access to knowledge intensive business services is valuable and results in higher productivity and growth providing that the firm has enough internal knowledge or absorptive capacity. The results also reveal that firms who are engaging in innovation activities persistently are endowed with higher absorptive capacity. Multiple measure of innovation and different definition of persistency have been tested.

Considering new firms formation and spinoff as a mechanism for knowledge spillover, the results suggest that there is heterogeneity even among the new firms; therefore successful policy needs to have broader view on entrepreneurship. Spinoffs which are distinct group of start-ups can inherit knowledge; but it is important to consider what type of knowledge and under which conditions this knowledge can be transferred to them.
References


Paper I
Innovation, Spillovers and Productivity Growth: A Dynamic Panel Data Approach

Hans Lööf*, Pardis Nabavi†

Abstract

This paper examines variation in productivity growth within a given location and between different locations. Implementing a dynamic panel data approach on Swedish micro data, we test the separate and complementary effect of internal innovation efforts and spillovers from the local milieu. Measuring the potential knowledge spillover by access to knowledge intensive services, the estimation results produce strong evidence of differences in the capacity to benefit from external knowledge among persistent innovators, temporary innovators and non-innovators. The results are consistent regardless of whether innovation efforts are measured in terms of the frequency of patent applications or R&D investments.

Keywords: Innovation, spillovers, TFP-growth, panel data
JEL-Codes: C23, O31, O32

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1 INTRODUCTION

Given the attention that firms’ engagement in research and innovation and their geographical location have attracted in the last decades, as well as the increased access to both detailed firm level data and regional data, surprisingly few studies have been able to assess the separate and complementary effect of these two production factors within the same framework.

In order to fill this gap, our paper provides empirical evidence on the impact of internal knowledge generation and knowledge spillovers from neighbouring firms on firms’ productivity growth. We proxy the first factor by the frequency of innovation efforts, and the second by the intensity of local knowledge sources.

In a dynamic framework, we then consider various innovation strategies in a particular location, and a particular innovation strategy in different locations. Using this methodology, we are able to test if firms with persistent frequency of innovation activities can overcome a low level of external knowledge potential, and whether a high external knowledge potential can compensate for a low level of internal knowledge.

Our empirical analysis applies to Swedish firm-level observations on manufacturing and service firms and we study two different time periods. In cases where patent applications are used to capture the innovation strategy (or internal knowledge generation) of the firm, the period studied extends from 1997 to 2008. In the second case, where R&D engagement information is used, the study employs survey data from three consecutive Swedish Community Innovation Surveys (CIS), covering the period 2002-2008. We use access to knowledge-intensive producer services as indicator for the mass or amount of influential external knowledge in the local milieu. In the empirical analysis, the paper identifies 35 Swedish producer-service industries at the 5-digit level in which
more than 30 per cent of employees have a university degree. These services include ICT services, engineering R&D and engineering services, financial services, and the brokerage and recruitment of manpower.

The estimation results produce strong evidence of differences in the capacity to benefit from external knowledge among persistent innovators, temporary innovators and non-innovators. The results are consistent regardless of whether innovation efforts are measured in terms of the frequency of patent applications or R&D investments. We do not find any differences in growth among non-innovative firms across locations, while the growth rate increases with the access to external knowledge for innovative firms.

The remainder of the paper is organised as follows: the next section discusses the relevant literature on internal and external knowledge and clarifies our theoretical assumptions. It also presents the hypotheses to be tested. Section 3 describes the data, and Section 4 introduces the testing strategy and the associated model specifications. Section 5 discusses and interprets the main findings, and Section 6 concludes.

2 LITERATURE REVIEW

The objective of our research is to clarify the idea of a symbiotic relationship between research and innovation (R&I) and spillovers by distinguishing between different levels and combinations of internal and external knowledge. In this section we will briefly review literature on heterogeneity and persistence concerning firms’ productivity and innovation activities. We then consider literature on spatial proximity to knowledge with business potential. Finally, we discuss the literature on knowledge-intense producer service and its role in the process of knowledge spillovers.
Innovation, persistency, and performance

A growing body of empirical literature documents the existence of performance heterogeneity across firms and establishments. This observation remains valid for several performance measures, including profitability, productivity and growth (Bartelsman and Doms, 2000). To a large extent, the heterogeneity also tends to persist over long periods (Mueller, 1986; Cubbin and Geroski, 1987; Geroski and Jacquemin, 1988; Geroski, 1998; Gschwandtner, 2005; Syverson, 2004, 2011; Dosi, 2007). Surveying the micro literature, Dosi and Nelson (2010) find that the heterogeneous productivity pattern can be explained by different abilities to innovate and/or adopt innovations developed elsewhere.

Previous studies have documented that, in most fields of innovation and technology, progress is cumulative in the sense that today’s efforts build on preceding efforts. Prior experience from related projects can create internal capabilities within organisations, and learning economies and these categories of internal spillovers tend to reduce the costs of new innovation (Nelson and Winter, 1982; Attewell, 1992; Cohen and Levinthal, 1990; Åstebro, 2002; Phene and Almeida, 2008; Teece, 2010). Thus, the continuity of innovation efforts ensures the accumulation of internal knowledge, whereas disruption can cause the erosion and obsolescence of acquired skills, routines and technology.

The overall picture that emerges from recent empirical studies, however, indicates that many firms are not at all engaged in innovation and R&D activities: some are innovation-active only occasionally, and others remain persistently innovation-active over periods of years (Cefis and Orsenigo, 2001; Klette and Kortum, 2004; Peters, 2009; Peters et al., 2013; Duguet and Monjon, 2002).

The literature provides various explanations for firms’ selection into persistence of innovation or not. One element of the literature stems from evolutionary
theory and emphasises the importance of technological trajectories. Along the technological trajectory, firms learn by innovating and developing organisational competencies (Raymond et al., 2010). Other explanations include the relationships between innovation and market power or financial constraints as selection mechanisms (Brown and Petersen, 2009).

**Communication externalities**

Firms do not learn solely from internal spillovers across projects and time. A common element of many theoretical propositions in the productivity literature and related economic models (Marshall, 1890; Arrow, 1962; Jacobs, 1969; Porter, 1990; Romer, 1986) is the hypothesis that a firm or an industry benefits from spatial proximity to knowledge. The presence of external knowledge flows should reveal itself in social returns to innovation efforts in addition to private returns\(^1\). Numerous studies have clarified that the social rate of return is larger in agglomeration areas, and that knowledge flows decline in volume and intensity as the distance between origin and destination increases\(^2\) 3.

A local environment with a wide spectrum of knowledge resources and a wide range of qualifications and competence profiles regarding the labour supply pro-

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1In a recent analysis based on technology flows across industries, Wolff (2012) finds that the direct rate of return to R&D in the US between 1958 and 2007 was 22%, whereas the indirect rate of return to R&D was 37%.

2Friction costs vary for both non-market spillover and commercial transfers because of communication distances. Distance frictions increase when knowledge is complex (Beckmann, 2000) and when it is tacit (Polany, 1966). Knowledge also has a tendency to be spatially sticky (von Hippel, 1994).

3Consistent with predictions from gravity models, Glaeser and Gottlieb (2009) estimate that the elasticity of income with respect to city size in the U.S. is within the range of 0.04–0.08 for different model specifications. The size of the estimates is comparable with estimates by Ciccone and Hall (1996), who find that a doubling of employment density in a country results in a 6% increase in average labour productivity. Using patent data, several studies indicate that the number of cross-citations significantly decreases as distance increases (Maurseth and Verspagen 2002, Verspagen and Schoenmakers 2000). Testing hypotheses on variety, Penken, Van Oort, and Verburg (2007) report that Dutch regions with a high degree of related variety had the highest rates of growth in employment. Focusing explicitly on innovations, Brouwer et al. (1999) demonstrate that firms located in agglomerated Dutch regions tend to produce larger numbers of new products than firms located in more rural regions. Similar result is reported by Doloreux and Shearmur (2012).
vides rich opportunities for knowledge exchange and creative interaction between firms and individuals. As a rule, these features apply to large urban regions in which the knowledge potential is higher than elsewhere. The importance of proximity between suppliers and buyers of knowledge-intensive producer services can be linked to the theory of agglomeration economies in large urban regions, according to which large regions offer companies more positive externalities than small regions. Fujita and Thisse (2002) describe this phenomenon as “communication externalities”. They measure the extent of the agglomeration advantage of a single firm by the company’s accessibility to other companies.

Recent studies provide evidence for the thesis that importance of access to external knowledge tends to increase in a knowledge-based innovation-driven economy. In their survey of literature on knowledge spillovers and local innovation system, Breschi and Lissoni (2001) argue that when firms are constantly innovating there is the need to be close to a constellation of allied firms and specialised suppliers to smooth input-output linkages. Consistent with this reasoning, several works suggest that a focus only on internal knowledge and the development of internal capabilities and routines is no longer sufficient for coping with challenges such as shorter product life cycles, greater technological complexity, more specialised knowledge and increasing cost. Therefore, firms need to tap into external knowledge sources. See, for instance, Czarnitzki and Hottenrott (2009), who find that highly skilled labour and the proximity to suppliers matter for firms’ innovation performance in Belgium. Similar results are provided by Saito and Gopinath (2011). Studying spillovers among Chilean manufacturing industries, they report that an increase in regional knowledge stock is the most effective policy to improve a plant’s productivity.
**Functional specialisation and complementarities**

Recent empirical evidence suggests a growing business potential from local supply of business service due to knowledge spillovers. A key explanation is that their service is shared by different firms and in different sectors. This development is especially prevalent in urban environments. Based on U.S. data, Duranton and Puga (2005) show that the increasingly strategic role of business services in the economy reflects an ongoing change in the features of urban system from specialising by sector to functional specialisation. Abundance of business service employment “gives strong incentives from cities to shift from a main specialisation along a sector dimension to a main specialisation along a function dimension” (Duranton and Puga 2005: 365). Larger cities are becoming more specialised in management functions and other producer services, whereas smaller cities are more specialised in manufacturing.

Duranton and Puga (2005) distinguish between three broad categories of business services: standard business (e.g. banking or equipment leasing), sophisticated business services (e.g. specialized financial advising), routinised business services (e.g. call centres). Only the two former benefit from geographical proximity and the business potential is related to complementary skills among the customers. A growing number of papers have studied the complementarities between internal knowledge and external knowledge acquisitions. The main result of this research questions the assumption that all firms in a milieu such as a cluster or an agglomeration may benefit from access to a high concentration of specialized, supplemented or varied knowledge diffused through voluntary (mostly pecuniary) and involuntary mechanisms. Typically, the empirical studies find that internal knowledge generation through R&I and external knowledge acquisitions are complements and emphasise the importance of in-house capacity for absorbing external knowledge, consistent with seminal papers by Cohen
Based on the findings from the literature discussed above, our a priori assumption in this paper is that firms with much internal knowledge, as measured by persistent innovation activities, are better placed to assimilate external local knowledge. Following the works by Duranton and Puga (2005), Kolko (1999), Ota and Fujita (1993), Davis and Henderson (2008) and others, we will exploit the ideas of business services as an indicator of external local knowledge. Our precise measure is producer-service industries and like our predecessors, we distinguish between simple and advanced services. To do that, we consider industries at the five-digit level in which more than 30 percent of the employees have a university degree. Producer services generally represent market-supporting services that improve the allocating efficiency of the economy and thus enhance productivity of individual firms. Knowledge-intensive producer services expand the potential for firms to interact with a wide range of knowledge-intensive services, providing rich opportunities for knowledge exchange and creative interaction that eventually results in technological development based on process and/or product innovation. In both cases, the buyer of the services will benefit from agglomeration externalities because knowledge-intensive service firms seek to sell their services and specialised knowledge to more than one client company, indirectly transmitting novel concepts and solutions from one customer to another.

A non-negligible fraction of the knowledge flows across firms are related to links outside the nearby milieu of the firms. Several strands of previous studies address this issue, such as the literature on (i) multinational corporations (e.g., Almeida and Phene 2012; Nobel and Birkinshaw 1998), (ii) strategic alliances and R&D collaboration (Hagedoorn 2002; Belderbos et al. 2012), (iii) urban

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economics (Saxenian 1990; Almeida 1996) and (iv) cognitive proximity (Nooteboom et al. 2007; Lychagin et al. 2010). Although the question of knowledge flows from more distant locations is beyond the scope of our study, we account for remote knowledge diffusion to some extent by including foreign and domestic multinational corporate ownership among the controls.

3 DATA AND VARIABLES

In our empirical investigation, we use manufacturing and service firm-level data provided by Statistics Sweden. The database contains accounting information on all firms in Sweden, information on the educational background and wages of their employees and the location of the firms.

The analysis applies information about the entire population of firms in the Swedish business sector with at least one employee, and the entire population of employees within these firms in the following ways. First, we calculate the aggregate earnings (wage sum) in each of Sweden’s 290 municipalities for all 35 industries that are classified as knowledge-intensive producer services (a list of these industries is provided in the Appendix Table A.1). This is our proxy for external knowledge potential. Second, we assign a value of access to potential knowledge to each firm in the Swedish business sector based on the particular municipality in which they are located. Third, we separate the firm’s into three evenly distributed groups based on their potential access to external knowledge. One-third of each of the approximately 400,000 existing Swedish firms are located in places defined as high accessibility areas and they are concentrated in 25 municipalities. An additional third of these firms are found in 78 municipalities classified as areas with medium access to potential external knowledge, and the remaining firms are located in 187 municipalities with low access to po-
tential external knowledge. With this approach, we capture both the individual firm’s proximity to nearby knowledge and the firm’s proximity to other firms with similar access to knowledge-intensive producers.

As a second step, we form two panels of firms. In the first panel (i.e., the patent panel), we have matched patent data to the entire population of firms in the Swedish business sector, whereas we match R&D data from the Community Innovation Survey (CIS) in the second panel (i.e., CIS panel). The preferred patent panel is restricted to firms with at least 10 employees on average over the 1997-2008 period. The restriction is motivated by our ambition to compare the empirical analysis using this panel with the same empirical approach applied to CIS data. In Sweden, 10 employees is the lower size limit for participation in the CIS studies.

For the patent panel, we use information from the European Patent Office’s worldwide patent statistical database (PATSTAT) complemented with data from the Swedish Patent Office. The panel consists of 40,524 unique firms, approximately 2,000 of which applied for at least one patent between 1997 and 2008. The CIS panel considers only those firms that participated in at least two of three consecutive Community Innovation Surveys (CIS) for 2004, 2006 and 2008. The matched data contain 2,738 unique firms. Both panels are unbalanced, and the second is observed only for the 2000-2008 period.

Using national and international patent applications, we classify firms as persistent innovators, occasional innovators and non-innovators based on observations over the entire 12-year period in the patent panel. An obvious limitation of employing CIS data in a panel setting is that almost all the information pertains only to particular years. One of the few exceptions is the frequency of R&D engagement, where the perspective comprises the most recent three-year period. However, such a period is also too short for the purposes of our research.
extend this information, we construct a data set from three different waves of the CIS survey. In the resulting CIS panel, 40% of firms are observed in all three surveys, and 60% are observed in two surveys. With overlapping data from the three surveys, we can observe the selected firms’ innovation strategies over a 5-7 year period.5

Table 1 presents summary statistics for the 1997-2008 period, with firms separated into three groups reflecting their long-term innovation strategies. Consider first the patent panel in Columns 1, 3 and 5. If a firm applied for a patent during 6 years or more6, we categorise the firm as a persistent innovator. If it applied for a patent in 1-5 years, we consider it an occasional innovator. Firms with no patent applications are non-innovators. The table also reports the corresponding statistics for firms observed in the CIS surveys in Columns 2, 4 and 6. We classify a firm as a persistent innovator for the whole 1997-2008 period if it is reported to be a persistent R&D investor in at least two surveys. Moreover, the firm is classified as non-innovative if it is never reported to be R&D-active. All other firms are considered to be occasional innovators.

In the patent panel, which includes all the approximately 40,000 relevant firms in Sweden, 95% are classified as non-innovative, 4% are classified as occasional innovators and 1% are classified as persistent innovators. In the CIS panel, 45% of firms are defined as non-innovative, 38% are occasional innovators and 17% are persistent innovators.

Consistent with our assumptions based on the literature review in Section 2, the median values of most variables differ for persistently innovative firms com-

5 However, the observations for the years 1997-1999 are utilised to obtain lags of the dependent variables. It should be noted that the panel is unbalanced in the sense that we include two voluntary surveys and one compulsory survey, which can cause some selection bias. For instance, the fraction of innovators is 31% in the CIS 2008 data and 54%, on average, in the CIS 2004 and 2006 data.

6 For a robustness check, 8 years threshold instead of 6 years is also considered. The results are similar.
Table 1: Descriptive statistics for 1997-2008. Innovation strategy based on patent applications and the CIS-panel (median and standard errors reported)

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<tr>
<td></td>
<td>Patent CIS panel</td>
<td>Patent CIS panel</td>
<td>Patent CIS panel</td>
</tr>
<tr>
<td>TFP growth a,c</td>
<td>0.032 (0.47)</td>
<td>0.028 (0.39)</td>
<td>0.025 (0.49)</td>
</tr>
<tr>
<td></td>
<td>0.026 (0.39)</td>
<td>0.025 (0.53)</td>
<td>0.023 (0.44)</td>
</tr>
<tr>
<td>Human capital b</td>
<td>0.036 (0.17)</td>
<td>0.026 (0.14)</td>
<td>0.071 (0.19)</td>
</tr>
<tr>
<td></td>
<td>0.053 (0.17)</td>
<td>0.145 (0.21)</td>
<td>0.111 (0.21)</td>
</tr>
<tr>
<td>Firm size a</td>
<td>2.83 (0.98)</td>
<td>2.94 (1.22)</td>
<td>3.56 (1.30)</td>
</tr>
<tr>
<td></td>
<td>3.43 (1.38)</td>
<td>(1.62)</td>
<td>4.73 (1.75)</td>
</tr>
<tr>
<td>Firm size growth</td>
<td>0.013 (0.38)</td>
<td>0.012 (0.29)</td>
<td>0.005 (0.31)</td>
</tr>
<tr>
<td></td>
<td>0.012 (0.29)</td>
<td>(0.28)</td>
<td>(0.29)</td>
</tr>
<tr>
<td>Physical capital a,c</td>
<td>13.69 (2.89)</td>
<td>14.20 (2.96)</td>
<td>14.82 (2.62)</td>
</tr>
<tr>
<td></td>
<td>14.80 (2.65)</td>
<td>16.28 (2.75)</td>
<td>16.32 (2.75)</td>
</tr>
<tr>
<td>Domestic Non Affiliate Firms</td>
<td>0.44</td>
<td>0.40</td>
<td>0.20</td>
</tr>
<tr>
<td>Domestic Unational Firms</td>
<td>0.34</td>
<td>0.32</td>
<td>0.23</td>
</tr>
<tr>
<td>Domestic Multinational Firms</td>
<td>0.12</td>
<td>0.14</td>
<td>0.36</td>
</tr>
<tr>
<td>Foreign Multinational Firms</td>
<td>0.10</td>
<td>0.14</td>
<td>0.21</td>
</tr>
<tr>
<td>High tech manufact b</td>
<td>0.01</td>
<td>0.04</td>
<td>0.07</td>
</tr>
<tr>
<td>Medium-High tech manu b</td>
<td>0.05</td>
<td>0.11</td>
<td>0.27</td>
</tr>
<tr>
<td>Medium-Low tech manu b</td>
<td>0.08</td>
<td>0.15</td>
<td>0.21</td>
</tr>
<tr>
<td>Low tech manu b</td>
<td>0.10</td>
<td>0.24</td>
<td>0.12</td>
</tr>
<tr>
<td>Knowledge-intense serv b</td>
<td>0.27</td>
<td>0.17</td>
<td>0.14</td>
</tr>
<tr>
<td>Other serv b</td>
<td>0.46</td>
<td>0.26</td>
<td>0.18</td>
</tr>
<tr>
<td>Mining b</td>
<td>0.03</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>Observations total</td>
<td>296,105</td>
<td>12,926</td>
<td>13,323</td>
</tr>
<tr>
<td>Unique firms</td>
<td>38,703</td>
<td>1,246</td>
<td>1,422</td>
</tr>
<tr>
<td>Observations, fraction</td>
<td>0.95</td>
<td>0.45</td>
<td>0.04</td>
</tr>
</tbody>
</table>

Note: a)Log, b)Fraction, c)Real prices
pared with firms with no innovation activity or only temporary engagement. Persistently innovative firms are larger than occasionally innovative firms, they have more physical capital, and higher intensities of human capital as well. They are also more likely to belong to multinational groups. Corresponding differences are observed between firms classified as occasionally innovative and non-innovators. With respect to growth rates, the descriptive statistics indicate no differences between the two categories of innovative firms, and the median TFP growth rate is highest for non-innovators. In contrast, only innovative firms grow in size. The table also reveals that persistent innovators are more oriented toward high technology and medium-high technology than other firms.

Table 2 displays the distributions of the 66,719 observed patent applications across markets, firm sizes, corporate ownership groups and sectors. The vast majority of patent applications are related to firms with more than 100 employees, a large fraction of which are multinational enterprises (MNEs). Domestic MNEs account for nearly 60 per cent of the applications, and foreign-owned MNEs account for 35 per cent. The most patent-intensive sectors are high and medium-high technology firms in the manufacturing sector. Knowledge-intensive services are more likely to apply for patents than are low or medium-low technology manufacturing firms, whereas the opposite is true for other services.

Table 3 reports the transition matrix with year-to-year changes in firms’ locations over the two samples. The locations are nearly time-invariant across firms with different innovation strategies and firms with different degrees of access to external knowledge. More than 99 per cent of firms remain in one place over any two consecutive years.
Table 2: Distribution of the patent applications during the 1997-2008 period by firms in Sweden across regions and groups

<table>
<thead>
<tr>
<th>Number of Applications</th>
<th>Occasional R&amp;I, %</th>
<th>Persistent R&amp;I, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge access: Low</td>
<td>6,947</td>
<td>0,25</td>
</tr>
<tr>
<td>Knowledge access: Medium</td>
<td>31,089</td>
<td>0,05</td>
</tr>
<tr>
<td>Knowledge access: High</td>
<td>28,590</td>
<td>0,06</td>
</tr>
<tr>
<td>10-25</td>
<td>3,308</td>
<td>0,47</td>
</tr>
<tr>
<td>26-99</td>
<td>5,860</td>
<td>0,32</td>
</tr>
<tr>
<td>100&gt;</td>
<td>57,458</td>
<td>0,03</td>
</tr>
<tr>
<td>Domestic Non Affiliate Firms</td>
<td>2,427</td>
<td>0,39</td>
</tr>
<tr>
<td>Domestic Uninational Firms</td>
<td>2,301</td>
<td>0,37</td>
</tr>
<tr>
<td>Domestic Multinational Firms</td>
<td>38,364</td>
<td>0,05</td>
</tr>
<tr>
<td>Foreign Multinational Firms</td>
<td>23,534</td>
<td>0,05</td>
</tr>
<tr>
<td>High tech manufacturing</td>
<td>31,572</td>
<td>0,02</td>
</tr>
<tr>
<td>Medium-High tech manufacturing</td>
<td>16,361</td>
<td>0,10</td>
</tr>
<tr>
<td>Medium-Low tech manufacturing</td>
<td>5,510</td>
<td>0,15</td>
</tr>
<tr>
<td>Low tech manufacturing</td>
<td>3,549</td>
<td>0,14</td>
</tr>
<tr>
<td>Knowledge-intense services</td>
<td>7,202</td>
<td>0,12</td>
</tr>
<tr>
<td>Other services</td>
<td>2,339</td>
<td>0,35</td>
</tr>
<tr>
<td>Mining</td>
<td>93</td>
<td>0,22</td>
</tr>
</tbody>
</table>

Table 3: Transition Matrix

<table>
<thead>
<tr>
<th>Access to external knowledge</th>
<th>No Occasional R&amp;I, %</th>
<th>Occasional R&amp;I, %</th>
<th>Persistent R&amp;I, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patent panel</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>99.3</td>
<td>99.6</td>
<td>99.1</td>
</tr>
<tr>
<td>Medium</td>
<td>99.1</td>
<td>99.1</td>
<td>99.3</td>
</tr>
<tr>
<td>High</td>
<td>99.4</td>
<td>98.9</td>
<td>99.0</td>
</tr>
<tr>
<td>CTS panel</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>99.5</td>
<td>99.5</td>
<td>99.6</td>
</tr>
<tr>
<td>Medium</td>
<td>99.5</td>
<td>99.1</td>
<td>99.5</td>
</tr>
<tr>
<td>High</td>
<td>99.4</td>
<td>98.9</td>
<td>99.5</td>
</tr>
</tbody>
</table>

Note: The matrix shows that all firms in all three categories of geographical areas tend to remain in the same place across time.
4 EMPIRICAL STRATEGY

General approach and hypotheses

The general approach of this paper is the following: First, we group the observed Swedish firms into three categories reflecting their internal knowledge. Second, the external knowledge potential of each firm is also arranged into three categories. These two steps allow us to classify the firms into nine different categories.

With regard to the internal knowledge, three classifications are defined. The first includes firms that do not engage in research and innovation activities (i.e., patent applications in one of the samples, and R&D in the other sample), and we consider their internal accumulated knowledge to be low. Our second group consists of firms that conduct R&I activities occasionally. Their accumulated knowledge is classified as medium. The final category includes firms that persistently engage in renewal efforts resulting in a high level of accumulated internal knowledge. The three categories are labelled $I_1$, $I_2$ and $I_3$, respectively.

For the external knowledge potential of each firm, we identify each firm’s access to the supply of knowledge-intensive producer services, which provides a knowledge potential value for every firm\(^7\). These values allow us to arrange all firms into three categories. The first category includes firms that belong to the lowest third of knowledge potential values. The second is firms that belong to the medium third of knowledge potential values, and the final category consists of firms that belong to the highest third of knowledge potential values. These three categories are labeled $K_1$, $K_2$ and $K_3$.

\(^7\)It should be noted that our knowledge potential indicator also announces the presence of other knowledge sources such as universities, research institutes, high-technology firms and creative capacities.
Based on the two sets of categories, we construct 9 combinatorial categories, as illustrated in Table 4. At one extreme, we find firms with low internal knowledge and low external knowledge potential ($IK_{11}$), and the firm at the other extreme has high internal knowledge intensity and high external knowledge potential ($IK_{33}$).

Table 4: Combinatorial categories of internal and external knowledge

<table>
<thead>
<tr>
<th></th>
<th>$I_1$</th>
<th>$I_2$</th>
<th>$I_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_1$</td>
<td>$IK_{11}$</td>
<td>$IK_{12}$</td>
<td>$IK_{13}$</td>
</tr>
<tr>
<td>$K_2$</td>
<td>$IK_{21}$</td>
<td>$IK_{22}$</td>
<td>$IK_{23}$</td>
</tr>
<tr>
<td>$K_3$</td>
<td>$IK_{31}$</td>
<td>$IK_{32}$</td>
<td>$IK_{33}$</td>
</tr>
</tbody>
</table>

Before we formulate the hypotheses precisely, we should observe that our formulation enables us to clarify the importance of each $IK$-combination. Therefore, we may for example investigate if a strong knowledge potential can compensate for a low level of internal knowledge. We can also determine if firms with persistent R&I efforts can compensate for a low level of external knowledge potential. Thus, we can contribute to the existing literature about the relative importance of the two knowledge factors in Table 4.

The first hypothesis refers to the combinatorial categories in the $I_1$-row, comprising firms with a low level of internal knowledge. More formally:

**H1**: There is no difference in the TFP growth for firms that belong to $IK_{11}$, $IK_{21}$, and $IK_{31}$, which implies that the local milieu and the external knowledge potential have no additional impact on firms with low internal knowledge.

Our second hypothesis concerns the $I_2$-row in Table 4, consisting of firms that make occasional R&D efforts:

**H2**: There is a difference in the TFP growth for firms that belong to the $I_2$ classification, such that $IK_{12} < IK_{22} < IK_{32}$. Thus, the growth rate of firms with occasional R&I is an increasing function of access to external knowledge.
potential.
The third group of firms is involved in persistent R&I efforts (I₃ firms), and the following hypothesis applies for these firms:

**H₃**: There is a difference in the TFP growth for firms that belong to the I₃ classification, such that $IK_{13} < IK_{23} < IK_{33}$. Thus, the growth rate of firms with persistent R&D is an increasing function of access to external knowledge potential.

Our remaining hypotheses consider only innovative firms. If such firms have the same external potential, we examine if persistent R&I firms are superior to occasional R&I firms. To accomplish this, we make pairwise comparisons between elements in the I₂ and I₃ columns.

**H₄**: Persistent R&D firms have higher TFP growth than firms with occasional R&D efforts, such that $IK_{13} > IK_{12}$, $IK_{23} > IK_{22}$, $IK_{33} > IK_{32}$. For all categories of location, there is always a positive improvement on TFP growth from more internal knowledge.

**Empirical model**

To quantify the relationship between TFP and the firm’s internal and external knowledge sources, we use an augmented Cobb-Douglas approach specified as a growth model. In doing so, we aim to capture the effect of a particular category of combined knowledge sources on the TFP growth, conditioned on the growth in the previous period and the TFP level in the previous period.

Total factor productivity growth is estimated in two steps. Following Levinsohn and Petrin (2003), we first compute TFP as the residual of the Cobb-Douglas production function, where the value added of the firm is the dependent variable and labour inputs (divided into highly educated and ordinary labour), material and physical capital are used as the determinants. In the next step, the growth
of TFP is estimated as a function of determinants inside and outside the firm as follows:

\[
\Delta \ln TFP = \alpha_0 + \left[ I_i \times K_i \right] \gamma_i + \beta_1 \Delta \ln TFP_{i,t-1} + \beta_2 \ln TFP_{i,t-1} + \\
\beta_3 \Delta \ln SIZE_{it} + \beta_4 \text{OWNER}_{it} + \beta_5 \text{SECTOR}_{it} + \mu_i + \tau_t + \varepsilon_{it}
\]  

(1)

where \( i \) indexes the firm, \( t \) the year, \( I \) is a vector of innovation indicators, \( K \) is a vector of external knowledge indicators, \( \Delta TFP \) is the annual growth rate of total factor productivity, TFP is the level of total factor productivity, \( \Delta SIZE \) is employment growth, and \( \text{OWNER} \) is corporate ownership. Additionally, the TFP growth depends on the sector, and we distinguish between six manufacturing and service sectors. The firm and year-specific effects are denoted by \( \mu \) and \( \tau \), respectively. Finally, \( \varepsilon \) is the idiosyncratic error term.

The key coefficient of interest is \( \gamma_i \), which determines the response of productivity growth to nine combinatorial categories of internal and external knowledge. It is useful to note that the key variable \( IK \) for firm \( i \) is almost constant over the period we observe due to the following explanation. First, the \( I \)-classification is based on the frequency of innovation efforts during the observed period, which means that it does not vary between years. Second, the \( K \)-classification is based on the knowledge intensity of the firm’s location, which is close to 100% identical between year \( t \) and year \( t+1 \) according to the transition matrix reported in Table 3.

Based on a procedure suggested by Papke and Wooldridge (2005), we also compute the coefficients and standard errors for long-run effects. The long-run effect is a nonlinear function of the coefficients of the explanatory variables and the lagged dependent variable in Equation (1).

To estimate Equation (1), we use the two-step system GMM estimator developed
by Arellano and Bover (1995) and Blundell and Bond (1998). This approach combines equations in differences of the variables with equations in levels of the variables. The validity of the instruments in the model is evaluated with the Sargan–Hansen test of over-identifying restrictions whereas the Arellano-Bond autoregressive test is used for identifying possible second-order serial correlation. An advantage with the system GMM estimator is that it requires fewer assumptions about the underlying data-generating process and uses more complex techniques to isolate useful information (Roodman, 2009). The estimator allows for a dynamic process, with current realisations of the TFP variable influenced by past TFP, and some regressors may be endogenous. Moreover, the system GMM estimator also accounts for individual specific patterns of heteroskedasticity and serial correlation of the idiosyncratic part of the disturbances.

Our preferred model treats the key variable $IK$ as exogenous due to the characteristics of this variable as discussed above. However, in an alternative regression, we consider the composite variable for knowledge combination as endogenous. We also report pooled OLS results for the dynamic model.

5 REGRESSION RESULTS

Table 5 presents estimates of Equation (1) using a two-step dynamic GMM estimator with the total factor productivity growth (TFP) as the dependent variable. Two alternative sets of results are displayed in the appendix. Table A.2 reports the GMM estimates, and Table A.3 reports the OLS estimates. Columns 1 and 2 report short- and long-run estimates for the sample that include the entire population of firms with an average of 10 or more employees over the period 1997-2008, whereas Columns 3 and 4 report the corresponding estimates for the CIS population, which is restricted to a stratified sample with a firm
size of 10 or more employees in the year of the surveys. The first panel is labelled the patent panel, and here we use patent applications as a proxy for innovation activity. The second panel is labelled the CIS panel, and in this case the innovation indicator is R&D engagement. The key-results are presented in the upper part of the table which is organized in three different panels. In the first panel, rows 1-3 show results for non-innovative firms. In the second, rows 4-6 show coefficients for temporary innovators. The third panel presents TFP growth with respect to persistently innovative firms in different locations in rows 7-9.

**Basic results**

Using $IK_{11}$ in Table 5 as reference group, the estimates in the first panel are small in absolute value and statistically significant only in the first column, showing the GMM estimates for the typical non-innovative firm located in regions with a medium intensity of external knowledge. In this case innovation is proxied by patent and the sign of the coefficient is negative. The first conclusion, however, is that there are no or almost no growth effects from pure and pecuniary spillovers for non-innovators, regardless of the panel, innovation indicator or estimator we consider.

The table reveals three results about rows 4-6 and firms temporarily engaged in innovation activities and with low, medium or high accessibility to outside knowledge in the local milieu. First, the estimates are positive and significantly different from the base-group for the patent panel. Second, the growth rate is markedly higher among temporary innovators in milieus where firms have high access to knowledge sources, compared to identical firms in milieus with medium or low access to external knowledge (0.067 versus 0.025 and 0.029, respectively). Third, the CIS-panel results are similar but weaker, with coefficients that are
positive but insignificant or only weakly significant. The final important set of results presented in Table 5 concerns the TFP growth among persistent innovators. Rows 7-9 provide a consistent picture for both samples. First, persistent innovators always have faster TFP growth than other firms, regardless of location. Second, the growth rate for persistent innovators increases with access to external knowledge. Consequently, the size of the estimates is largest for the average persistent R&I firms located in areas with high access to external knowledge. The magnitude of the estimate is 0.221 in the patent sample and 0.139 in the CIS sample.

Table 5 also presents the long-run estimates for the two samples, given in Columns 2 and 4, and these results are by default fully consistent with the short-run estimates in Columns 1 and 3. Examining the covariates displayed in Table 5, we find negative signs for both TFP growth and TFP level in the previous year. While the latter indicates a tendency to convergence in line with predictions from growth theory, the former deserves some comments. Why is growth in a given year a negative function of last year’s growth rate in our data? There might be a possibility that firms in general simply follow a quiet-life behaviour pattern. Hence, the improvement in the performance yesterday reduces the incentives for firms to invest their efforts in better performance (growth) today. Instead they decide to enjoy the fruits of their earlier activities. For a discussion on similar findings, see Hashi and Stojić (2013).

In contrast to the preferred patent panel, the alternative CIS panel contains a smaller proportion of firms with falling productivity, because the panel is a selected group of surviving firms over a 4-7 year period. This difference between the panels is also reflected in the TFP estimate for the CIS panel, which is indeed negative but close to zero (0.036) and insignificant. Turning to other controls, one noteworthy but not unexpected result is that multinational firms
Table 5: Dependent variable: TFP growth, two-step system GMM estimates

<table>
<thead>
<tr>
<th>Innovation variable</th>
<th>PATENT PANEL</th>
<th>CIS PANEL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Short-run</td>
<td>Long-run</td>
</tr>
<tr>
<td>IK\textsuperscript{a}</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>IK\textsuperscript{b}</td>
<td>-0.008**</td>
<td>-0.01**</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>IK\textsuperscript{b}</td>
<td>0.002</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>IK\textsuperscript{b}</td>
<td>0.029***</td>
<td>0.02***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>IK\textsuperscript{b}</td>
<td>0.025**</td>
<td>0.02**</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>IK\textsuperscript{b}</td>
<td>0.067***</td>
<td>0.06***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>IK\textsuperscript{b}</td>
<td>0.082***</td>
<td>0.07***</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>IK\textsuperscript{b}</td>
<td>0.126***</td>
<td>0.11***</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>IK\textsuperscript{b}</td>
<td>0.221***</td>
<td>0.19***</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Log Firm size, growth</td>
<td>0.021</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>(0.072)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Log TFP growth\textsubscript{t-1}</td>
<td>-0.147**</td>
<td>-0.036</td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>Log TFP\textsubscript{t-1}</td>
<td>-0.239***</td>
<td>-0.383***</td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.107)</td>
</tr>
<tr>
<td>Domestic Uninational\textsuperscript{b}</td>
<td>0.033**</td>
<td>0.03**</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Domestic multinational\textsuperscript{b}</td>
<td>0.083***</td>
<td>0.07***</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Foreign multinational\textsuperscript{b}</td>
<td>0.099***</td>
<td>0.086***</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Observations</td>
<td>196,027</td>
<td>20,076</td>
</tr>
<tr>
<td>Unique firms</td>
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<td>2,634</td>
</tr>
<tr>
<td>Laglimits</td>
<td>(3 1)</td>
<td>(3 2)</td>
</tr>
<tr>
<td>Instruments</td>
<td>93</td>
<td>81</td>
</tr>
<tr>
<td>AR(2)</td>
<td>0.914</td>
<td>0.206</td>
</tr>
<tr>
<td>Hansen Overid.</td>
<td>0.231</td>
<td>0.178</td>
</tr>
<tr>
<td>Diff-in-Hansen test level eq.</td>
<td>0.846</td>
<td>0.192</td>
</tr>
<tr>
<td>Diff-in-Hansen test lag dep.</td>
<td>0.299</td>
<td>0.107</td>
</tr>
</tbody>
</table>

Note: * significant at 10%; ** significant at 5%; *** significant at 1%
Robust (GMM) standard error in parentheses. Year and sector dummies included
(a) Reference group (b) Reference group is domestic non-affiliated firms

\textsuperscript{a}[IK\textsubscript{11}: Non R&I and Low access]; [IK\textsubscript{12}: Non R&I and Medium access]; [IK\textsubscript{13}: Non R&I and High access]
\textsuperscript{b}[IK\textsubscript{21}: Occ R&I and Low access]; [IK\textsubscript{22}: Occ R&I and Medium access]; [IK\textsubscript{23}: Occ R&I and High access]
\textsuperscript{a}[IK\textsubscript{31}: Pers R&I and Low access]; [IK\textsubscript{32}: Pers R&I and Medium access]; [IK\textsubscript{33}: Pers R&I and High access]
have a higher growth rate than other firms, *ceteris paribus*. The TFP growth is notably neutral with respect to firm size, even after controlling for internal and external knowledge.

The test statistics are reported in the lower part of Table 5. We use lag limits t-3 instruments for the regression in differences in both panels and lagged differences dated t-1 for the regression in levels in the patent panel and t-2 in the CIS panel. This results in 93 instruments in the patent panel regression and 81 instruments in the CIS panel regressions, which are both within a reasonable range. The AR(2) test rejects the presence of second-order autocorrelation in the first-differenced residuals in both regressions. Otherwise, the GMM estimator could be inconsistent. The Hansen J-test of over-identifying restrictions confirms that the instruments are valid, and the difference-in-Hansen test confirms that the additional instruments required for systems estimation are valid for the two regressions.

**Wald test of the predictions**

Overall, the results in Table 5 indicate a strong, positive relationship between proximity to knowledge and persistent R&I (innovation activities measured by patent or R&D). To evaluate the quantitative importance of the *IK* coefficients in detail, we conduct a Wald test on the equality of means in Table 6. The first prediction from our hypotheses H1-H4 is that the local milieu and the external knowledge potential have no additional impact on firms with low internal knowledge. The H1 section of the table indicates that non-innovators in places with medium access to knowledge outside the firm have only somewhat lower growth rates than the reference group (non-innovators in locations with low access to external knowledge) in the patent panel. No significant difference is found in the CIS panel. We therefore confirm Hypothesis 1.
Our second prediction, that the growth rate of firms with occasional R&I is an increasing function of access to external knowledge, is partly confirmed when the patent panel is considered in the H2 portion of Table 6. Temporary innovators in high-access areas are growing faster than temporary innovators located in other places. However, no significant difference exists in the equality of growth means between firms that are occasionally engaged in places with low and medium access to external knowledge. We also find no significant difference in the coefficients with respect to location in the CIS panel. Thus, we cannot confirm hypothesis H2 based on the CIS panel and only partly when we use the patent panel.

Table 6: T-test on the equality of means reported as p-values

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>Patent panel</th>
<th>CIS panel</th>
</tr>
</thead>
<tbody>
<tr>
<td>IK_{13} = IK_{12}</td>
<td>H1</td>
<td>0.003***</td>
</tr>
<tr>
<td>IK_{13} = IK_{11}</td>
<td>H1</td>
<td>0.008**</td>
</tr>
<tr>
<td>IK_{23} = IK_{22}</td>
<td>H2</td>
<td>0.004***</td>
</tr>
<tr>
<td>IK_{23} = IK_{21}</td>
<td>H2</td>
<td>0.006***</td>
</tr>
<tr>
<td>IK_{22} = IK_{21}</td>
<td>H2</td>
<td>0.667</td>
</tr>
<tr>
<td>IK_{33} = IK_{32}</td>
<td>H3</td>
<td>0.008***</td>
</tr>
<tr>
<td>IK_{33} = IK_{31}</td>
<td>H3</td>
<td>0.000***</td>
</tr>
<tr>
<td>IK_{32} = IK_{31}</td>
<td>H3</td>
<td>0.039**</td>
</tr>
<tr>
<td>IK_{33} = IK_{23}</td>
<td>H4</td>
<td>0.000***</td>
</tr>
<tr>
<td>IK_{32} = IK_{22}</td>
<td>H4</td>
<td>0.000***</td>
</tr>
<tr>
<td>IK_{31} = IK_{21}</td>
<td>H4</td>
<td>0.017**</td>
</tr>
</tbody>
</table>

Note: The table report t-test for hypotheses H1-H4. P-values and degrees of significance are reported. * significant at 10%; ** significant at 5%; *** significant at 1%

IK_{11}: Non R&I and Low access; IK_{12}: Non R&I and Medium access; IK_{13}: Non R&I and High access
IK_{21}: Occ R&I and Low access; IK_{22}: Occ R&I and Medium access; IK_{23}: Occ R&I and High access
IK_{31}: Pers R&I and Low access; IK_{32}: Pers R&I and Medium access; IK_{33}: Pers R&I and High access

We turn to the prediction that the growth rate of firms with persistent R&I is an increasing function of access to external knowledge (H3). The results for the patent panel indicate that persistent innovators in high access (knowledge) re-
regions are growing significantly faster than corresponding firms in both medium- and low-access regions. Moreover, persistent innovators in medium-access places have higher growth rates than persistent innovators in low-access locations.

The CIS panel indicates that persistent innovators in areas with high access to external knowledge are growing significantly faster than the corresponding firms with low access to external knowledge. However, we cannot conclude that the estimation for persistent innovators in places with high access to external knowledge (0.159) is significantly larger than the coefficient for persistent innovators in locations with medium access (0.123) or that the medium-access estimate is greater than the estimate for low access (0.094). The overall assessment based on the estimation of the two panels is that we cannot reject the third hypothesis.

Our final prediction (H4) is that a positive return to improvement of internal knowledge always applies for all categories of location, which implies that persistent innovators outperform occasional innovators in all types of locations. The prediction is strongly confirmed in both of our panels.

**Sensitivity analysis**

One concern with the results presented in Table 4 is the possibility that the key-variable $IK$ might be considered to be endogenous and that an exogenous shock might affect both the TFP-growth of the firms and their choice of location. Although the transition matrix reported in Table 4 indicates that the likelihood of a firm moving between our three location categories is very low, this concern is partially addressed in Table A2 by rerunning Equation (1) and dropping the exogenous assumption on the interaction-variable $IK$. However, the instrument for the $IK$-variable is not meaningful because by construction the variables are almost completely identical to the variable itself. Despite this methodological
In Table A2, we undertake an analysis of the TFP growth using the endogeneity assumption of the nine IK variables. The key results in Table A2 are changed substantially as a result of the different treatment of the IK variable. The estimates for non-innovators in places with medium and high access to external knowledge and for occasional innovators across all regions as well as the coefficients for persistent innovators in regions with low access to external knowledge are not significantly different from the reference group. In sharp contrast, the estimates for persistent innovators in locations with medium and high access to knowledge are considerably larger than for those obtained from the preferred GMM specification. These two estimates are large and significant in both the patent panel and the CIS panel.

The most marked difference in the GMM results, depending on whether we are treating the IK variable as exogenous or endogenous, obtains for the occasional innovators. While Table 5 shows some limited influence from the surrounding local environment, Table A2 reports that these estimates are insignificant. This result also applies to persistent innovative companies in geographic environments with low external knowledge intensity.

Table A3 in the appendix indicates that the pooled OLS estimates of Equation (1) produce the same overall results as the more efficient dynamic GMM estimates. The main difference is the sizes of the estimates, which are lower when using the OLS estimator. The estimator suffers from dynamic panel data bias as well as bias due to serial correlation in the error term and potential endogeneity.

What then are the common observations in the three tables? Table 5 and Tables A2 and A3 in the appendix reveal four regularities that persist in alternative specifications and estimators. First, the differences in the coefficient estimates

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8A fixed-effect model is used to estimate the lag of the dependent variable for all regressions. The results indicate that the coefficients on lagged dependent variables using the GMM estimator are higher than the coefficients obtained for the fixed effect model and lower than the OLS estimates. The results are available upon request.
among non-innovators in different locations are negligible. Second, our evidence that occasionally innovative companies grow faster in a knowledge-intensive environment is weak. Third, the growth rates for persistently innovative firms in locations with high access to external knowledge are always higher than those of firms in other locations, regardless of innovation strategy. Finally, for persistent innovators, the growth rates are always increasing with the amount of external knowledge.

Although all three regressions suggest economically important effects of internal and external knowledge on TFP growth for persistent innovators, only the preferred GMM model and the OLS estimates also indicate positive effects for temporary innovators in places with high access to external knowledge. However, the latter finding is only relevant for the patent sample. Overall, proximity appears to be more important for innovative firms, consistent with our a priori assumption.

6 CONCLUSIONS

Our study aims to illuminate the separate and combined effect of innovation and potential spillovers from a growth perspective. A significant amount of prior research supports the view that (i) a firm’s knowledge is a key competitive asset (Grant, 1996), (ii) continuity of innovation efforts ensures the accumulation of internal knowledge (Dosi and Nelson, 2010), (iii) very few firms, if any, can internally develop all critical knowledge needed for growth (Almeida and Phene, 2012), (iv) a firm’s potential for exploiting external knowledge and recombining internal and external knowledge increases with its own knowledge stock (Cohen and Levinthal, 1990), and (v) locational proximity to external knowledge reduces the cost and increases the frequency of contacts with players in a net-
work (Saxenian, 1990). Building on these and similar findings, we construct a simple analytical model that examines how firms exploit internal knowledge in conjunction with external knowledge to gain productivity growth.

We model knowledge inputs in a production function by using a discrete composite variable with nine different combinations of the intensity of knowledge from within and from outside the firm. Internal knowledge is measured by the frequency of national and international patent applications. We have matched patent applications to all 40,524 unique manufacturing and service firms in Sweden with an average of 10 or more employees from 1997 to 2008. A second alternative panel is constructed from an overlapping data set from three Swedish Community Innovation Surveys in 2004, 2006 and 2008 for which 2,738 manufacturing and service firms participated in at least two of the three surveys. In this case, the data are restricted to firms with at least 10 employees during the year of the survey.

To find a proxy for knowledge flow across firms, we identify 35 different Swedish knowledge-intense producer-service industries at the five-digit level in which the share of employees with university degree is above 30 percent. These services include ICT services, engineering R&D and engineering services, financial services, and brokerage and recruitment of manpower.

Applying a dynamic GMM estimator to the data, which also includes extensive firm characteristics on human capital, physical capital, employment, ownership and sector classification, two equations were estimated. The main findings are as follows:

- The local milieu and the external knowledge potential have no additional productivity growth impact on firms with low internal knowledge.
- The growth rate of total productivity is only weakly associated with ex-
ternal knowledge for firms with occasional innovation efforts.

- The growth rate of total productivity is strongly associated with external knowledge for firms with persistent innovation efforts.
- All location categories exhibit improvement of internal knowledge.

Our study provides new empirical knowledge about the systematic differences of firms’ capability to benefit from external knowledge. It also suggests a method for capturing and quantifying the extent of knowledge flows across firms. Moreover, the study demonstrates the appropriateness of using the increasingly popular dynamic GMM estimator to control whether productivity and growth results are due to observed heterogeneous characteristics of firms and places or factors such as unobserved heterogeneities or true or false state dependence.

The above findings have implications for both policy and management. With our approach, the results indicate that the benefits of knowledge-intensive local milieus are not uniformly distributed across different types of firms. We find strong effects on TFP growth only for innovating firms and especially for persistent innovators. We do not detect any substantial effect for occasional innovators and no effect at all for non-innovators, which constitute the vast majority of all firms. Thus, while the policy debate tends to assume that firms located in knowledge-rich milieus such as urban agglomerations and specialized spatial clusters will profit from proximity to diversified knowledge and supply of knowledge-intensive producer services, in technology, law, finance, management, marketing and other support functions, the study contributes to a more nuanced discussion. Our distinct results support recent studies suggesting that policymakers and managers should not expect that the presence of a knowledge-intensive environment automatically leads to leverage effects on firm
performance. Instead, supportive innovation policies should consider measures that help to maintain and improve the knowledge milieu of places in which many firms follow strategies that give priority to a permanent innovation engagement. The result from our study also raises the complex question: which policies can facilitate the transition of a firm from a state of being an occasional innovator to being persistently engaged in innovation efforts? Occasional efforts include disruptions that can cause the erosion and obsolescence of acquired skills, routines and technology. The policy nexus of our study is two-pronged. A firm’s knowledge management comprises (i) systematic accumulation of internal knowledge combined with the development of absorption and accession capacity, and (ii) location in a knowledge-intensive environment. The basic policy message is that these two components are not substitutes, but rather complements.

There are several limitations of this study that can become questions for future research. First, the issue of knowledge flows across firms that are not related to links within the nearby milieu of the firms is not explicitly addressed in this paper, except for the effect associated with multinational company groups. Recently Cantwell and Piscitello (2015) have used openness of the regional industry and the regional economy to capture global knowledge diffusion, while other papers apply methods such as trade statistics, patent citations and strategic alliances. A second issue that deserves a more subtle analysis than is provided in the present paper is the internal mechanisms for creating and maintaining conduits to the external environment that facilitates knowledge flows to the firm. Another issue for future research is to investigate the importance of the corporate ownership. Are multinational firms more efficient at exploiting external local knowledge than other firms? Is there any difference in the ability to benefit from the nearby milieu between domestically owned firms and foreign firms?
References


A Appendix
### Table A.1: Knowledge intense producer services with more than 30% knowledge intensity in 2007

<table>
<thead>
<tr>
<th>SIC 2002 Industry</th>
<th>Knowledge Fraction intensity, % KIPS30</th>
</tr>
</thead>
<tbody>
<tr>
<td>7220                               Software consultancy and supply</td>
<td>46.1</td>
</tr>
<tr>
<td>74202                              Construction and other engineering activities</td>
<td>38.4</td>
</tr>
<tr>
<td>65120                              Monetary intermediation</td>
<td>32.5</td>
</tr>
<tr>
<td>74140                              Business and management activities</td>
<td>45.2</td>
</tr>
<tr>
<td>74120                              Accounting, book-keeping &amp; auditing activities</td>
<td>41.2</td>
</tr>
<tr>
<td>72210                              Publishing of software</td>
<td>30.3</td>
</tr>
<tr>
<td>73501                              Labor recruitment activities</td>
<td>35.9</td>
</tr>
<tr>
<td>73102                              R&amp;D on engineering and technology</td>
<td>68.5</td>
</tr>
<tr>
<td>74111                              Legal advisory</td>
<td>70.9</td>
</tr>
<tr>
<td>74850                              Secretarial and translation activities</td>
<td>32.9</td>
</tr>
<tr>
<td>65220                              Credit granting</td>
<td>31.7</td>
</tr>
<tr>
<td>61102                              Sea and coastal water transport</td>
<td>42.8</td>
</tr>
<tr>
<td>74201                              Architectural activities</td>
<td>67.1</td>
</tr>
<tr>
<td>73103                              R&amp;D medical and pharmaceutical science</td>
<td>69.7</td>
</tr>
<tr>
<td>73101                              R&amp;D on natural science</td>
<td>74.3</td>
</tr>
<tr>
<td>74104                              R&amp;D on agricultural science</td>
<td>67.1</td>
</tr>
<tr>
<td>74130                              Market research and public opinion pulling</td>
<td>36.1</td>
</tr>
<tr>
<td>74872                              Design activities</td>
<td>32.4</td>
</tr>
<tr>
<td>67120                              Security broking and fund management</td>
<td>52.7</td>
</tr>
<tr>
<td>60012                              Life insurance</td>
<td>33.8</td>
</tr>
<tr>
<td>67202                              Activities auxiliary to insurance and pension funding</td>
<td>31.6</td>
</tr>
<tr>
<td>72400                              Data base activities</td>
<td>31.7</td>
</tr>
<tr>
<td>65232                              Unit trust activities</td>
<td>36.5</td>
</tr>
<tr>
<td>65231                              Investment trust activities</td>
<td>49.7</td>
</tr>
<tr>
<td>74122                              Advisory activities concerning patents and copyrights</td>
<td>30.2</td>
</tr>
<tr>
<td>73201                              R&amp;D on social science</td>
<td>79.9</td>
</tr>
<tr>
<td>73202                              R&amp;D on humanities</td>
<td>80.1</td>
</tr>
<tr>
<td>74150                              Management activities of holding companies</td>
<td>34.9</td>
</tr>
<tr>
<td>67110                              Administration of financial markets</td>
<td>48.6</td>
</tr>
<tr>
<td>65110                              Central banking</td>
<td>54.0</td>
</tr>
<tr>
<td>66020                              Pension funding</td>
<td>40.6</td>
</tr>
<tr>
<td>73105                              Interdisciplinary R&amp;D on natural science &amp; Eng.</td>
<td>69.9</td>
</tr>
<tr>
<td>65210                              Financial leasing</td>
<td>31.2</td>
</tr>
<tr>
<td>73201                              Interdisciplinary R&amp;D on humanities &amp; social science</td>
<td>77.8</td>
</tr>
<tr>
<td>70110                              Development of selling of real estate</td>
<td>40.5</td>
</tr>
</tbody>
</table>
Table A.2: Dependent variable: TFP growth, two-step system GMM estimates.
The IK-variable is treated as endogenous

<table>
<thead>
<tr>
<th>Innovation variable</th>
<th>PATENT PANEL</th>
<th>CIS PANEL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Short-run</td>
<td>Long-run</td>
</tr>
<tr>
<td>IK11&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>IK12</td>
<td>0.016</td>
<td>0.01</td>
</tr>
<tr>
<td>IK13</td>
<td>-0.004</td>
<td>-0.00</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>IK21</td>
<td>-0.001</td>
<td>-0.00</td>
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<tr>
<td></td>
<td>(0.111)</td>
<td>(0.09)</td>
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<tr>
<td>IK22</td>
<td>-0.106</td>
<td>-0.08</td>
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<tr>
<td></td>
<td>(0.171)</td>
<td>(0.13)</td>
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<tr>
<td>IK23</td>
<td>-0.103</td>
<td>-0.08</td>
</tr>
<tr>
<td></td>
<td>(0.168)</td>
<td>(0.13)</td>
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<tr>
<td>IK31</td>
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<tr>
<td></td>
<td>(0.252)</td>
<td>(0.19)</td>
</tr>
<tr>
<td>IK32</td>
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<td>0.14***</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.04)</td>
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<tr>
<td>IK33</td>
<td>0.687***</td>
<td>0.54***</td>
</tr>
<tr>
<td></td>
<td>(0.196)</td>
<td>(0.16)</td>
</tr>
<tr>
<td>Log Firm size, growth</td>
<td>0.242***</td>
<td>0.27***</td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Log TFP growth&lt;sub&gt;_t−1&lt;/sub&gt;</td>
<td>−0.270***</td>
<td>−0.209***</td>
</tr>
<tr>
<td>Log TFP&lt;sub&gt;_t−1&lt;/sub&gt;</td>
<td>−0.220***</td>
<td>−0.339***</td>
</tr>
<tr>
<td>Domestic Uninational&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.039***</td>
<td>0.03***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Domestic multinational&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.103***</td>
<td>0.08***</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Foreign owned multinational&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.116***</td>
<td>0.09***</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.02)</td>
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<td>Observations</td>
<td>196,027</td>
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<td>Unique Firms</td>
<td>31,208</td>
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<td>Laglimits</td>
<td>(3 1)</td>
<td>(2 1)</td>
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<tr>
<td>Instruments</td>
<td>193</td>
<td>217</td>
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<tr>
<td>AR(2)</td>
<td>0.106</td>
<td>0.894</td>
</tr>
<tr>
<td>Hansen Overid.</td>
<td>0.831</td>
<td>0.779</td>
</tr>
<tr>
<td>Diff-in-Hansen test for level</td>
<td>0.652</td>
<td>0.509</td>
</tr>
<tr>
<td>Diff-in-Hansen test for lag dep.</td>
<td>0.389</td>
<td>0.596</td>
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</tbody>
</table>

Note: * significant at 10%; ** significant at 5%; *** significant at 1%
Robust (GMM) standard error in parentheses. Year and sector dummies included

[a] Reference group  [b] Reference group is domestic non-affiliated firms

IK<sub>11</sub>: Non R&amp;I and Low access; IK<sub>12</sub>: Non R&amp;I and Medium access; IK<sub>13</sub>: Non R&amp;I and High access
IK<sub>21</sub>: Occ R&amp;I and Low access; IK<sub>22</sub>: Occ R&amp;I and Medium access; IK<sub>23</sub>: Occ R&amp;I and High access
IK<sub>31</sub>: Pers R&amp;I and Low access; IK<sub>32</sub>: Pers R&amp;I and Medium access; IK<sub>33</sub>: Pers R&amp;I and High access
Table A.3: Regression results pooled OLS estimates, dependent variables: TFP growth.

<table>
<thead>
<tr>
<th>Innovation variable</th>
<th>TPF growth</th>
<th>TPF growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PATENT</td>
<td>CIS</td>
</tr>
<tr>
<td><strong>IK_{11}^{a}</strong></td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td><strong>IK_{12}</strong></td>
<td>-0.004**</td>
<td>-0.006</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.007)</td>
</tr>
<tr>
<td><strong>IK_{13}</strong></td>
<td>0.004*</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.008)</td>
</tr>
<tr>
<td><strong>IK_{21}</strong></td>
<td>0.016***</td>
<td>-0.001</td>
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<tr>
<td></td>
<td>(0.006)</td>
<td>(0.007)</td>
</tr>
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<td><strong>IK_{22}</strong></td>
<td>0.011</td>
<td>0.005</td>
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<tr>
<td></td>
<td>(0.008)</td>
<td>(0.008)</td>
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<td><strong>IK_{23}</strong></td>
<td>0.042***</td>
<td>0.011</td>
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<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
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<tr>
<td><strong>IK_{31}</strong></td>
<td>0.034***</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.011)</td>
</tr>
<tr>
<td><strong>IK_{32}</strong></td>
<td>0.073***</td>
<td>0.040***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.012)</td>
</tr>
<tr>
<td><strong>IK_{33}</strong></td>
<td>0.155***</td>
<td>0.075***</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Log Firm size, growth</td>
<td>0.310***</td>
<td>0.191***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Log TFP growth_{t-1}</td>
<td>-0.330***</td>
<td>-0.343***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Log TFP_{t-1}</td>
<td>-0.125*</td>
<td>-0.134***</td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Domestic Uninational^{b}</td>
<td>0.015***</td>
<td>-0.009*</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Domestic multinational^{b}</td>
<td>0.044***</td>
<td>0.031***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Foreign owned multinational^{b}</td>
<td>0.055***</td>
<td>0.036***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Observations</td>
<td>196,027</td>
<td>20,076</td>
</tr>
</tbody>
</table>

Note: * significant at 10%; ** significant at 5%; *** significant at 1%
Robust standard error in parentheses. Year and sector dummies included.

(a) Reference group (b) Reference group is domestic non-affiliated firms

IK_{11}: Non R&I and Low access; IK_{12}: Non R&I and Medium access; IK_{13}: Non R&I and High access
IK_{21}: Occ R&I and Low access; IK_{22}: Occ R&I and Medium access; IK_{23}: Occ R&I and High access
IK_{31}: Pers R&I and Low access; IK_{32}: Pers R&I and Medium access; IK_{33}: Pers R&I and High access
Paper II
The Joint Impact of Innovation and Knowledge Spillovers on Productivity and Growth for Exporting Firms

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1. INTRODUCTION

A primary issue in the literature on exports is the incidence of learning from global customers. A less explored aspect is the extent to which exporters can learn from their local milieu and the possible differences between persistent innovative exporters and other exporters in this respect.

International economic theories predict that the most innovative domestic firms enter the export markets (Grossman and Helpman, 1995). Therefore, there is a growing interest in better understanding the mechanism behind innovation among scholars who study the world economy. In this respect, they consult various branches of the literature on technological change that attempt to explain why firms become innovative and why some firms remain innovative year after year. This paper contributes to the analysis within this tradition. To examine how the local milieu influences the performance of exporters, we relate the level and growth of total factor productivity (TFP) to the combined effects of internal innovation activities and external knowledge that can be accessed from the firm’s local environment.

In contrast to the conventional economic wisdom that innovation is an exogenous random shock similar to manna falling from heaven, the economics of innovation consider innovation to be a deliberate and intentional result of a firm’s ability to generate new knowledge and create new products and processes (Antonelli et al., 2013). According to the Schumpeterian approach, rivalry pushes firms to innovate to survive. The higher the competitiveness of the rivals within the same industry, the more likely a firm is to rely on the introduction of innovation to be competitive (Aghion et al., 2005).

Enquiries about knowledge generation processes have revealed that innovative firms are more able to learn in the subsequent attempts to generate new knowledge (Nelson, 1959; Stiglitz, 1987; David, 1993). This phenomenon has been described in terms of ‘standing on the shoulders of giants’, which means that firms are able to learn from their existing stock of knowledge (Caballero and Jaffe, 1993). Consequently, the positive effect on current and future innovation costs is an increasing function of the size of the accumulated stock of knowledge (Arrow, 1969). A further element in this learning process is the presence of sunk costs for the long-term investments in the research infrastructure, which creates major entry and exit barriers to the market (Sutton, 1991).

A number of studies on trade that use micro-data confirm the theoretical predictions that innovation is associated with the likelihood of entering the export market (Cassiman and Golovko, 2011), and there is strong empirical evidence that innovative exporters account for a disproportionally large share of exports. The data used in the present paper, for instance, show that less than one in three Swedish exporters introduced at least two new products into the
export market over a 12-year period. However, these firms accounted for almost 90 per cent of the total export value.

The obvious conclusion from our Swedish data is that exporters are not necessarily innovators, at least not on a regular basis. We observe that less than 10 per cent of the exporting firms in Sweden applied for patents in two or more years during the 12-year period of the study, and a large fraction of the exporters continue to offer similar product assortments to customers year after year.

How can we explain the presence of firms with low or no innovative activity in export markets? One possible explanation is that these firms have capabilities other than innovation that influence their ability to absorb and assimilate external knowledge on technology, markets and others. This acquired external knowledge may, in turn, affect the competitiveness of products with less novelty in international markets. This could involve, for example, customising an existing product for new or specific uses or finding new customers for an existing product.

In this paper, we study how exporters can learn from their local milieus by estimating a dynamic model using data collected from nearly 10,000 Swedish exporting firms. Different innovation proxies are used, and we distinguish between persistent and non-persistent innovators, while knowledge from outside the firm is measured with a newly developed methodology with detailed spatial resolution. The econometric evidence shows that persistent innovators benefit significantly more than other exporters from access to a rich spectrum of nearby knowledge. However, we also find positive effects of externalities among non-innovative exporters or exporters that are only occasionally engaged in innovation activities, provided that these firms are located in the most knowledge-intense milieus.

The remainder of the paper is organised as follows: Section 2 provides a background of the relevant literature and specifies the specific research questions. Section 3 presents the data, and the empirical approach is set out in Section 4. Section 5 reports the results, and the main implications are discussed in the concluding section.

2. LITERATURE REVIEW AND HYPOTHESES

a. Innovation and Knowledge Externalities

Guided by theoretical foundations, a growing body of literature observes detailed firm-level activities among firms that operate in international markets to estimate how innovation affects different forms of performance. This literature includes self-selection into exports (Girma et al., 2004), international knowledge spillovers (Keller, 2009), learning by exporting (Van Biesebroeck, 2005), and the causality between innovation and exports (Damijan et al., 2010). Two dimensions that have been investigated only in a very small number of studies from this literature include: (i) the difference between persistently innovative firms and other exporters and (ii) the opportunity to learn from the local milieu.

A firm’s ability to innovate is a central component in the processes of gaining and sustaining competitive advantage in regional, national and global markets. Empirical studies demonstrate that innovative firms have characteristics similar to those of exporters, including higher profits, increased productivity (and often higher productivity growth relative to other firms), better credit ratings and greater chances of survival in the market (Hall, 2011).

An important aspect of firms’ innovation engagement is the persistence of renewal efforts. Specifically, continuity in development efforts facilitates knowledge accumulation, whereas
disruptions to research and development (R&D) engagements can cause the results of previous efforts to be lost. Continuity ensures the maintenance of both innovation routines and knowledge. Similarly and simultaneously, persistent innovation efforts increase the stock of knowledge assets and create internal spillovers over time, which decreases the relative costs of new innovations (Geroski et al., 1997; Klette and Kortum, 2004; Hall, 2007; Cohen, 2010; Dosi and Nelson, 2010).

For quite a long time, economists have been aware of knowledge externalities as an unpaid external production factor in the production function (Marshall, 1920; Griliches, 1979). Knowledge spillovers are also a fundamental element in the models of endogenous growth based on the free utilisation of knowledge generated outside the firm but within the economic system (Romer, 1990; Lucas, 2009). Building on this idea, streams of literature consider the firm primarily as a knowledge integrator where the creation of new technological knowledge by each firm consists of the recombination of existing internal knowledge and knowledge generated in other firms (Weitzman, 1996; Antonelli, 2013).

The implicit background of this paper is the foundation laid out by the substantial literature on technical change and organisational learning that shows that technological development constantly pressures firms to increase their demand for knowledge and skills (Tushman and Anderson, 1986; Acemoglu, 2002; Almedia and Phene, 2012). Theoretical and empirical research predicts and confirms that increasingly complex technical knowledge creates a growing gap between what firms actually know and what they must know to be competitive (Coase, 1937; Grant, 1996; Tsang, 1997; Cantwell and Zhang, 2012; Huber, 2012).

Krugman (1991) suggests that spillovers cannot be easily measured and tracked because knowledge flows are invisible to a large extent. However, more recent research has made important progress in the attempt to disentangle this external production factor. For instance, a range of empirical studies show that the social rate of return differs across locations and that knowledge flows diminish in volume and intensity as the distance between the origin and destination grows. In this paper, we address this issue by examining whether the potential benefit from incoming spillovers differs in various locations between more innovative exporters and less innovative exporters.

In the economics of technical change, devoting a greater amount of internal effort to innovation has long been recognised to lead to a greater capacity to benefit from technological externalities (Nelson and Winter, 1982; Cohen and Levinthal, 1990; Cassiman and Veugelers, 2006; Phene and Almeida, 2008). These firms’ capabilities include experience, skills and organisational routines for the development and accession of knowledge pertaining to technical solutions and for associated renewal activities aiming at innovating and adopting new technical solutions.

In their survey of the literature on knowledge spillovers and local innovation systems, Bre-schi and Lisaioni (2001) discuss an emerging strand of research that suggests that firms do not necessarily need to have their own in-house knowledge as long as they have access to that knowledge. Acquisition of external knowledge may substitute for a firm’s own R&D investment under certain circumstances. (See for instance Barney, 1991; Audretsch and Feldman, 1996; Lavie, 2006). However, consistent with Chesbrough and Teece (1996), most studies emphasise that the efficiency of open resource systems requires that firms have sufficient in-house knowledge.

A growing number of studies show that a firm can access external knowledge in different ways. The knowledge may be purchased or transferred under a licence contract, it can move into the firm by hiring new employees who bring know-how and knowledge of technical
solutions from places in which they worked earlier in their careers, and it can spill over from national and/or international collaborative efforts with different customers, partners and specialised producer services.

Feldman (1994) demonstrates that the presence of specialised business services is another possible diffusion channel. Both knowledge-intensive producer services and other types of producer services represent a growing share of all of the jobs in the economy, with the largest share located in urban agglomerations. This process of growth is stimulated by outsourcing processes in which companies externalise standard routine services and specialised knowledge services, in addition to an increased general demand for knowledge in manufacturing and service production. Because the mission of producer service firms is to sell their services and specialised knowledge to more than one client company, novel concepts and solutions are indirectly transmitted from one customer to another.

Rigby and Zook (2002) suggest that the ability to combine internal and external information sourcing as a critical new source of competitive advantage in fast-growing industries. This discussion has been followed up in the series of more recent studies. Cantwell and Zhang (2012) introduce the concept of a knowledge accession strategy, which implies that the generation of new knowledge is a process that combines and recombines current and acquired knowledge from sources both inside and outside the firm. External knowledge can be accessed in both a firm’s local milieu and the global environment.

Recent literature on external knowledge sourcing proposes that firms increasingly rely on distinctively local knowledge sources (Nelson, 1993; Almeida, 1996; Murmann, 2003). Such reliance appears to be consistent across the entire range of size classes from very small (Acs et al., 1994) to very large firms (Rugman, 2000; Gassler and Nones, 2008). However, the literature on absorptive capacity states that the ability to absorb and assimilate external knowledge is closely related to internal knowledge capacity.

The findings above can be summarised as follows: There is broad consensus among economists that favourable local conditions may lead to increased productivity. However, a long line of empirical studies shows that the social rate of return differs across locations and that knowledge flows diminish in volume and intensity as the distance between origin and destination grows. Moreover, firms differ in the capacity to exploit the pool of local knowledge, and this difference can be linked to internal innovation efforts.

b. Hypotheses

Based on the literature reviewed in this section, we derive three parallel hypotheses for the conjunction of internal and external knowledge that is tested in the empirical analysis. These hypotheses are identical for the analysis of variation in both TFP and TFP growth. Thus, regarding productivity and growth, we propose the following hypotheses:

**H1 and H4:** Non-innovative or temporarily innovative exporters have internal capabilities that enable them to benefit from knowledge external to local knowledge. TFP (H1) and TFP growth (H4) increase with the intensity of external knowledge.

Although absorptive capacity can be closely linked to a firm’s internal knowledge generation through repeated innovation activities year after year, exporting firms have capabilities that not only differentiate them from firms that operate solely in domestic markets but are also reflected in a capacity to identify, absorb and assimilate knowledge external to the firm.
**H2 and H5:** A persistently innovative exporting firm will always be more productive (H2) and grow faster (H5) than a non-persistent innovator, regardless of location.

Substantial literature shows that the persistency of innovation is a distinct characteristic that separates a small fraction of firms from the majority of firms in terms of almost every critical performance measure. Therefore, a persistently innovating exporter located in a less favourable location will be more productive and grow faster than a less innovative firm in a dense external knowledge milieu.

**H3 and H6:** Among persistently innovative exporting firms, those located in the environments with the best access to external knowledge will have the highest TFP (H3) and the fastest TFP growth (H6).

Persistent innovation activities increase a firm’s stock of knowledge and create internal spillovers over time. A by-product of this process is a growing capacity to exploit incoming spillovers; the denser and richer the external knowledge, the better the conditions are for combining and re-combining current and acquired knowledge from in-house sources and knowledge from sources external to the firm.

### 3. DATA

**a. Construction of the Data Sample**

This study is based on register data for exporting manufacturing firms in Sweden retrieved from Statistics Sweden and data from the European Patent Office’s PATSTAT database supplemented with patent data from the Swedish Patent Office. The register data cover 100 per cent of Swedish firms and provide information on the firms’ value added, exports, employment, human capital (university-educated employees), physical capital, ownership, geographical location and industry classification; all national and international patent applications by firms in Sweden are included in the patent data. For the analysis, we have merged the data and restricted the observations to exporting manufacturing firms observed over the 1997–2008 period. Because there are quality problems in the export data for the smallest firms, only firms with an average of 10 or more employees over the 12-year period are considered.

**b. Innovation Indicators**

Our main interest is how exporting firms can learn from their local milieus and the possible differences between persistent innovative exporters and other exporters in this respect. Let us first ask what we mean by innovation.

One issue that arises when answering this question is that there is no widely accepted definition of innovation. This has motivated many on-going efforts to create better definitions of this term. In part, this work is conducted within the Organisation for Economic Co-operation and Development (OECD) and documented in the so-called Oslo Manual. According to the most recent manual, an innovation is ‘the implementation of a new or significantly improved product (good or service) or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations’ (OECD, 2005). However, there is a significant element of arbitrariness in this formulation. For instance, it is less clear from the Oslo Manual what can be called ‘new’ or ‘significantly improved’, what
the difference is between a radical innovation and an incremental innovation, or what distinguishes an innovation from an imitation.

In this paper, we choose to measure a firm’s innovative activities using three different proxies: (i) persistent presence in the export market; (ii) the regular renewal of export products and (iii) regular patent applications. Each of these proxies has its own flaws, but our a priori assumption is that all three proxies should provide similar – or at least non-conflicting – evidence. We consider the first indicator to be the weakest of the three because we can only assume, without being able to confirm, that a sustained presence in foreign markets requires continuous renewal. However, many recent studies use export experience as measure of knowledge processes within the firm (e.g. Cadogan et al., 2002; Blalock and Gertler, 2004). The two other measures are both provided in our data, and we consider patent applications to be the most significant indicator of a firm’s innovation activities in the analysis.¹

Our innovation variables are defined as follows: persistent presence in the export market refers to firms that never exit from the export market, renewal of products refers to firms that have introduced at least two new products to the export market during the 12-year period, and patent applications refers to firms that have applied for a patent in at least two of the 12 years covered in our observation period.

c. Localised Knowledge Base

There have been various attempts in the literature to capture knowledge external to a firm. In this paper, we rely on spatial resolution, as suggested by Johansson and Klaesson (2011) and Weibull (1976), for which information is available about the location of firms and the location of external knowledge sources. In such a setting, the following model formulation can be applied.

The model identifies locations \( i \) and \( j \) and explores information about the time distance \( t_{ij} \) between each such pair of locations and information about the size of a selected type of external knowledge source \( G \). For any firm in location \( i \), we define the firm’s time distance-weighted knowledge potential with regard to \( G_j \) (external knowledge in location \( j \)) as

\[
M_{ij} = \exp \left\{ -\lambda t_{ij} \right\} G_j.
\] (1)

where \( M \) is the potential external knowledge in location \( j \) that can be accessed by firms in location \( i \) and \( \lambda \) is an estimated parameter expressing time sensitivity for making face-to-face contacts between the two locations and is based on observed commuting behaviour. Using formula (1), we can also calculate the external knowledge of the local milieu using

\[
M_{ii} = \exp \left\{ -\lambda t_{ii} \right\} G_i.
\] (2)

and observing that contacts inside a location also have a time distance, signified by \( t_{ii} \). The knowledge-potential measures (\( M \)-values) can be given a probability interpretation such that equations (1) and (2) provide a measure of the expected knowledge contacts between actors

¹ Andersson and Johansson (2008) formulate a model in which new export varieties are assumed to reflect a firm’s innovation ideas. Regarding patents, Pakes and Griliches (1980) find a significant association between R&D and patents. Surveying the patent literature, Griliches (1990) reports support for the hypothesis that changes in R&D expenditures correlate with changes in the number of patents. Quantitatively, the elasticity of patents with respect to R&D typically clusters at approximately 0.5 (Blundell et al., 2002).
in location $i$ and knowledge sources in location $j$, as well as between actors in location $i$, based on random-choice behaviour or accessibility calculations (for more information on the estimated time distance parameters for Sweden, see Johansson et al., 2003).

Several knowledge resources may be reflected by the $G$ variable value in a given location: (i) the extent of university R&D (spending or man-years); (ii) the extent of R&D efforts made by private industry; (iii) the extent of R&D efforts made by the public sector; (iv) the number of patent applications and/or patents granted; (v) the supply of knowledge-intensive producer services (the employment or economic value of the supply); (vi) the number or value of exporters and importers and (vii) the number or value of export products and import products. A general observation is that different definitions of $G$ will frequently be highly correlated (Johansson and Lööf, 2014).

Alternative (v) has recently been applied by Johansson et al. (2013), who illuminate how firms can benefit from access to knowledge-intensive producers. This paper follows their approach and observes the aggregate wage sum of knowledge-intensive producer services in location $i$ and location $j$ as a proxy for knowledge external to the firm.\footnote{Table A1 in the appendix reports the five-digit industry codes that we use to calculate potential external knowledge.} This category of specialised business services comprises 35 different knowledge-intensive producer services at the five-digit level in which the share of employees with a university degree is above 30 per cent. These services include information and communication technology (ICT), R&D engineering, finance, brokerage and personnel recruitment.

In our application of the Johansson-Klaesson-Weibull measure, we separate all of the approximately 400,000 existing firms in Sweden into three equal groups with different levels of access to knowledge-intensive producer services in their regional milieu. We then observe the number of exporting firms in the groups. Table 2 shows that in total, approximately 52 per cent of exporters are located in regions in which the access to external knowledge is low, whereas approximately one-third (35 per cent) are located in regions with a medium level of access to knowledge, and only a small fraction (13 per cent) are located in milieus with a high level of access to knowledge regardless of their innovativeness.

Combining the observations on two different states of innovation activity (persistent or non-persistent) and three different types of firm locations (high, medium and low access to external knowledge), we create the interaction variable IS (internal innovation efforts and the spatially related knowledge external to the firm) and group the firms into six categories as specified in Table 1. In this classification, IS1 represents an extreme category in which firms make infrequent or no renewal efforts and the local milieu is characterised by low knowledge potential, whereas category IS6 consists of firms that are persistently engaged in renewal efforts and are located in areas with high knowledge potential.

There is a broad consensus in the literature that firm size is positively related to productivity because larger firms are in larger markets have greater economies of scale, greater scope and so forth. Table 2 also shows that innovators are substantially larger than other firms. To isolate the influence of size on productivity, we include the logarithm of the number of employees in both equations. In the modern growth literature, human capital and skilled labour are major factors of enhancing productivity, and the extensive empirical literature confirms the significant, positive relationship between physical investment and productivity. We estimate TFP by including human capital and physical capital as inputs. The controls also
include corporate ownership. Firms that belong to a multinational group stand out from others in terms of their propensity to conduct innovation projects and their ability to obtain positive results from their efforts. This phenomenon is frequently attributed to the diffusion of knowledge that occurs in a multinational group with widely spread intragroup networks. Finally, we control for export experience with the number of years the firm has been engaged in the export market, the industry classification of the firm at the two-digit level, and year dummies.

**d. Summary Statistics**

Table 2 provides summary statistics for different innovation proxies. The first section reveals the statistics for firms categorised as either non-persistent or persistent exporters, and each of these categories is distributed across three different types of locations: low, medium and high levels of access to external knowledge. In all, 51.3 per cent of the firms are non-persistent exporters, whereas 48.7 per cent of the firms exported every year.

The average exporting experience is six years for non-persistent exporters and approximately 10 years for persistent exporters (those firms that exported in all years in the study period, which includes both the entry and exit of firms). The middle section categorises firms by their capacity to introduce new products to the export market. We define a firm as innovative if it has introduced at least two new products in a 12-year period; the fraction of innovators decreases to 22.4 per cent with this criterion. The last section uses patent applications as the innovation proxy, and only 8.5 per cent of the firms applied for a patent in at least two years over the 1997–2008 period. The distribution of firm productivity shows that firm productivity increases with locations in more knowledge-intensive milieus for both innovators and other exporters, and the average level of productivity is highest in innovative firms for a given location. Regarding productivity growth, the summary statistics show no systematic pattern.

Across the different definitions of innovation, there is a clear pattern that innovative firms are larger than non-innovative firms in each type of location and that the average firm size is substantially higher in locations with a high degree of access to external knowledge for both innovators and non-innovators. Not surprisingly, the same pattern is also observed for human capital, and innovative firms have a higher intensity of human capital (i.e. the fraction of employees with at least three years of university education) compared with non-innovative firms in the same location. The summary statistics also reveal that the typical non-innovative exporter in low knowledge-intensive areas is a national firm, whereas global firms dominate among the innovative exporters in high knowledge-intensive locations. As shown in Table 2, the 48.7 per cent of the total firms that exported persistently during the 1997–2008 period accounted for 98 per cent of the total export value over that period. In addition, the 27
TABLE 2
Summary Statistics: Three Different Proxies for Innovative Exporters and Three Different Types of Locations. Sample Size = 9,580

<table>
<thead>
<tr>
<th></th>
<th>I. Persistent Exporters</th>
<th>II. New Export Products</th>
<th>III. Patents</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Some Years With no Exports 51.3%</td>
<td>Exporting All Years 48.7%</td>
<td>Identical Products 77.6%</td>
</tr>
<tr>
<td>Growth, log TFP (%)</td>
<td>4.3</td>
<td>3.9</td>
<td>3.6</td>
</tr>
<tr>
<td>EMP</td>
<td>34</td>
<td>52</td>
<td>102</td>
</tr>
<tr>
<td>Growth, EMP</td>
<td>0.90</td>
<td>0.81</td>
<td>0.62</td>
</tr>
<tr>
<td>HC (%)</td>
<td>2.9</td>
<td>5.5</td>
<td>9.9</td>
</tr>
<tr>
<td>EE</td>
<td>6.34</td>
<td>6.18</td>
<td>6.02</td>
</tr>
<tr>
<td>OW1</td>
<td>0.47</td>
<td>0.40</td>
<td>0.41</td>
</tr>
<tr>
<td>OW2</td>
<td>0.38</td>
<td>0.40</td>
<td>0.34</td>
</tr>
<tr>
<td>OW3</td>
<td>0.11</td>
<td>0.12</td>
<td>0.14</td>
</tr>
<tr>
<td>OW4</td>
<td>0.04</td>
<td>0.08</td>
<td>0.11</td>
</tr>
<tr>
<td>Sum</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Share of total Export (%)</td>
<td>0.7</td>
<td>1.0</td>
<td>0.4</td>
</tr>
<tr>
<td>Unique firms</td>
<td>2,313</td>
<td>1,793</td>
<td>810</td>
</tr>
<tr>
<td>Obs, total</td>
<td>19,364</td>
<td>13,755</td>
<td>5,531</td>
</tr>
<tr>
<td>Obs, fraction</td>
<td>0.26</td>
<td>0.18</td>
<td>0.07</td>
</tr>
</tbody>
</table>

Notes:
Standard errors in parentheses. TFP, Log total factor productivity; EMP, Log employment; PC, Log physical capital; HC, Human capital, fraction; EE, Export experience; OW1, Domestic non-affiliate enterprises; OW2, Domestic group enterprises; OW3, Domestic multinational enterprises and OW4, Foreign multinational enterprises.
per cent of total firms that introduced at least two new products during the covered period accounted for 86 per cent of the total export value of all firms, whereas the 8.5 per cent of total firms with two or more years of patent applications accounted for 56 per cent of the export value of all firms.

4. METHODOLOGY

The general methodology that we apply is a panel data approach, which allows for an interpretation of causality. The model has the following structure:

\[ y_{it} = \gamma_1 y_{i,t-1} + \beta_1 X_{it} + \lambda_t + \eta_i + \nu_{it}. \]  

(3)

where \( y \) is the dependent variable, \( X_{it} \) is a vector of the explanatory variables, \( \beta \) is a vector of the estimation coefficients associated with the explanatory variables, \( \lambda_t \) and \( \eta_i \) are time and firm-specific effects, respectively, and \( \nu_{it} \) denotes the model errors. The model is estimated with a dynamic generalised method of moments (GMM) instrumental variable approach (Arellano-Bond).

The analysis relies on TFP as a measure of firm productivity. TFP is computed as the residual of the Cobb-Douglas production function (Levinsohn and Petrin, 2003), where the firm’s value added is the dependent variable and labour inputs (divided into highly educated and ordinary labour) and material and physical capital are used as independent variables.

In relation to our estimation of TFP based on the study by Levinsohn and Petrin (2003), a concern may be noted that was raised by De Loecker (2010) in the context of exporting and learning by exporting (LBE). He claims that most tests of the existence of the LBE mechanism may be flawed. He notes that the usual empirical strategy is to examine whether productivity estimates, typically obtained as the residual of a production function estimation, increase after firms enter the export market. According to him, for such an estimate to make sense, past export experience should be allowed to impact future productivity. The research topic in our paper, however, is not LBE but a comparison of productivity and growth among persistent innovators and other exporters in three different locations. Given that our TFP variable should suffer from some of the problems discussed by Ackerberg et al. (2007), it should have a similar effect (bias) on both innovators and non-innovators. Moreover, the dynamic GMM model applied actually allows for the influence of past export experience on future productivity.

Thus, the variables that we wish to explain are TFP and TFP growth. Our primary interest is to determine the elasticity of productivity and growth with respect to a composite variable consisting of different alternatives for innovation combined with different levels of access to external knowledge. The following equations are used in this paper:

\[ y_{it} = \alpha_i + \alpha_j + \alpha_t + \gamma_1 y_{i,t-n} + \beta_1 IS_{it} + \beta_2 EMP_{i,t-n} + \beta_3 EE_{it} + \beta_4 OW_{it} + \epsilon_{it}, \]  

(4)

\[ \Delta y_{it} = \alpha_i + \alpha_j + \alpha_t + \gamma_1 \Delta y_{i,t-n} + \beta_1 IS_{it} + \beta_2 \Delta EMP_{i,t-n} + \beta_3 EE_{it} + \beta_4 OW_{it} + \epsilon_{it}, \]  

(5)

where the dependent variables are the log productivity \( (y_{it}) \) in equation (4) and the growth of log productivity \( (\Delta y_{it}) \) in equation (5). \( IS \) is the interaction variable between innovation and geographically related knowledge spillovers. There is a substantial degree of heterogeneity across the firms in our sample. The levels of productivity and productivity growth are higher in some industries than in others as a result of factors unrelated to innovation and location. Therefore, we allow for exogenous differences in productivity and growth across industries by
including the industry effect ($x_j$). We also include time-fixed effects ($x_t$) because our sample period covers fluctuations over the business cycle and, in particular, the ICT debacle of 2000–02. The third category of heterogeneity that we allow for is the fixed effects for individual firms ($x_i$). EMP is log employment, EE is export experience in years, OW is corporate ownership, and $\epsilon_i$ is the idiosyncratic error term. Because several papers show a persistent difference in productivity levels across firms (Dosi, 2007; Syverson, 2011), we also include the lagged labour productivity and lagged growth among the controls. Because we use human capital and physical capital in the first step to compute TFP, they are not included among the regressors in the TFP equations.

The econometric model that is used is a dynamic two-step system GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). To apply equations (4) and (5) within the GMM framework, we must classify the variables as endogenous, predetermined, weakly exogenous and strictly exogenous. Based on the literature, we treat the determinants of productivity and firm size (employment) as endogenous regressors. The endogeneity concern is a possible correlation between these variables and unobserved productivity shocks.

The interaction variable IS and other dummy variables are treated as exogenous in the model. It should be noted that the variation in IS over time is almost zero because the innovation strategy is constant, and most firms did not change location during the 12-year observation period. Finding a plausible instrument for this almost constant variable is not possible in the present application (for a similar case, see Lychagin et al., 2010).

5. RESULTS

The empirical models presented in Section 4 explain firms’ productivity and growth as a function of the combination of internal innovation activity and external knowledge while controlling for observed and unobserved firm characteristics. In this section, we present the empirical results. Table 3 reports the productivity estimates, while the growth rate estimates are presented in Table 4. A major distinction between persistent innovation activities (PI) and non-persistent innovation (NPI) is introduced. The latter category includes both occasional innovators and exporters with no observable innovations at all.

a. Level Regressions

Beginning with the level regressions shown in Table 3, the first column presents the results when the dichotomous innovation variable (PI vs. NPI) is observed as export persistency, column 2 reports innovation captured by new product statistics, and column 3 uses patent statistics to separate persistent innovators from exporters that engaged in innovations only temporarily or not at all.

The first three rows of the table report the estimated effect of the potential access to knowledge for firms defined as NPI exporters, while rows 4–6 repeat this presentation for PI exporters.

Using NPI in areas with low access to external knowledge as the reference group (IS1), the parameter estimates from estimating equation (4) show no significantly different results across the three columns for NPIs in municipalities characterised by medium level of access to external knowledge (IS2). In contrast, the coefficient estimates are positive and significantly different from the control group for NPIs located in milieus with a strong potential for spillovers from a knowledge-intensive area (IS3). Expressed in percentages, there is a location
<table>
<thead>
<tr>
<th></th>
<th>I. Export Persistency</th>
<th>II. New Products</th>
<th>III. Patent</th>
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<td>Log TFP</td>
<td>Log TFP</td>
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<td>IS1a</td>
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<td>Ref</td>
<td>Ref</td>
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<tr>
<td>IS2</td>
<td>0.008</td>
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<tr>
<td></td>
<td>(0.008)</td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>IS3</td>
<td>0.029**</td>
<td>0.025*</td>
<td>0.025**</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.013)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>IS4</td>
<td>0.010</td>
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<td>0.036</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.019)</td>
<td>(0.024)</td>
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<tr>
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<td>0.021</td>
<td>0.037*</td>
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<tr>
<td></td>
<td>(0.013)</td>
<td>(0.021)</td>
<td>(0.034)</td>
</tr>
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<td>IS6</td>
<td>0.061***</td>
<td>0.069*</td>
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<td>(0.029)</td>
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<td>(0.031)</td>
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<td>0.213</td>
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<td></td>
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<td>IS6=IS5</td>
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<td>0.185</td>
<td>0.174</td>
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</tr>
<tr>
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<td>0.015**</td>
<td>0.023**</td>
<td>0.007***</td>
</tr>
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<td>0.203</td>
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<td>0.017**</td>
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<td>0.867</td>
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<td>0.093*</td>
<td>0.016**</td>
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<td>0.14</td>
<td>0.052*</td>
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Notes:
(i) IS1, Non-innovation, low spillovers; IS2, Non-innovation, medium spillovers; IS3, Non-innovation, high spillovers; IS4, Innovation, weak spillovers; IS5, Innovation, medium spillovers; IS6, Innovation, high spillovers; EMP, Employment log; EE, Export experience; OW1, Domestic non-affiliate enterprises; OW2, Domestic group enterprises; OW3, Domestic multinational enterprises; OW4, Foreign multinational enterprises.
(ii) *Reference is domestic non-affiliate firms.
(iii) †Wald test p-values reported.
(iv) ***p < 0.01, **p < 0.05, *p < 0.1.
(v) Robust standard errors in parentheses.
(vi) Year dummies and two-digit sector dummies included.
(vii) The number of unique firms with three lags for the level equation is 6,882.
(viii) The total number of observations is 41,261.
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<td>Ref</td>
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<td>0.009</td>
<td>0.007</td>
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<td>0.078**</td>
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<td>(0.016)</td>
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<td>0.169***</td>
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<td>(0.016)</td>
<td>(0.030)</td>
<td>(0.052)</td>
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<td>0.123**</td>
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<td>0.030**</td>
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<td>(0.014)</td>
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<td>(0.046)</td>
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<tr>
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<tr>
<td>IS6=IS3</td>
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<td>0.009***</td>
<td>0.003***</td>
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<tr>
<td>IS6=IS2</td>
<td>0.001***</td>
<td>0.003***</td>
<td>0.002***</td>
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<td>0.060*</td>
<td>0.010***</td>
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<td>IS5=IS3</td>
<td>0.004***</td>
<td>0.005***</td>
<td>0.002***</td>
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<td>IS5=IS2</td>
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<tr>
<td>IS4=IS3</td>
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<td>IS4=IS2</td>
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<td>IS3=IS2</td>
<td>0.356</td>
<td>0.246*</td>
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Notes:
(i) IS1, Non-innovation, low spillovers; IS2, Non-innovation, medium spillovers; IS3, Non-innovation, high spillovers; IS4, Innovation, weak spillovers; IS5, Innovation, medium spillovers; IS6, Innovation, high spillovers; EMP, Employment log; EE, Export experience; TFP, Log total factor productivity; OW1, Domestic non-affiliate enterprises; OW2, Domestic group enterprises; OW3, Domestic multinational enterprises; OW4, Foreign multinational enterprises.
(ii) $^a$Reference is domestic non-affiliate firms.
(iii) $^b$Wald test $p$-values reported.
(iv) $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.
(v) Robust standard errors in parentheses.
(vi) Year dummies and two-digit sector dummies included.
(vii) The number of unique firms in the growth regression with three lags is 6,310.
(viii) The total number of observations is 34,358.

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premium of 2.5 to 2.9 per cent for non-persistent innovators in places with high knowledge proximity compared with the base group.

Thus, we cannot reject the first hypothesis that non-innovative or temporarily innovative exporters have internal capabilities that enable them to benefit from knowledge external to local knowledge. The interesting finding here is that we can document that exporting firms with no innovation or only occasional innovation have an internal capacity to take advantage of a favourable physical location in terms of the proximity to external knowledge. To our knowledge, this has not been demonstrated in previous studies.

Our second hypothesis is that PI exporters are always more productive than NPI exporters. While this is true for PI-exporting firms in areas with medium and high-potential external knowledge pools, the hypotheses do not hold for PI exporters in locations with low potential access to external knowledge. Comparing the estimates for IS4 in row 4 (PI exporters) with the estimates for IS3 in row 3 (NPI exporters), Table 3 reports higher coefficients for the latter category of firms when innovation is defined by both export intensity and the introduction of new products to the export market. Concerning the preferred patent measure, the size of the estimate is higher for PI firms in places with a small external knowledge pool compared with NPI firms in areas with a large knowledge pool, but the difference does not show statistical significance different from zero.

The third hypothesis is that the productivity of PI exporters is a positive function of the potential knowledge external to the firm. Comparing IS4, IS5 and IS6, the hypothesis is confirmed in all three columns reporting the results for different innovation proxies. This result is most distinctive when innovation is defined by patent applications. Recalculating the estimates in column 3 to percentages, we find that the productivity level is 5.3 per cent higher for the average persistent patenting firm in an area with a medium level of access to external knowledge compared with a corresponding firm in a location with limited knowledge (IS5 vs. IS4). The productivity difference is 9.3 per cent when comparing patenting firms in locations with high and low external knowledge intensity (IS6 vs. IS4). The equivalent differences in the second column (new products) and the first column (export persistency) follow the same tendency, but it is slightly smaller in size and only partially significant.

The results obtained for the controls show that TFP is a positive function of firm size and export experience (number of years in the export market), although the coefficient estimate is not significant for the latter. No statistically significant differences can be found among the four ownership variables. The bottom portion of Table 3 reports the test statistics for the GMM estimation. The AR(2) test reveals that the estimates are not biased by any presence of serial correlation, whereas the Hansen test reports that our 125 instruments that were chosen to account for endogeneity in the model are valid.

b. Productivity Growth

In Table 4, we examine hypotheses 4–6, which contemplate the relationship between TFP growth and the combination of internal and external knowledge. First considering non-innovative or temporarily innovative exporters, our prediction is that internal capabilities enable them to benefit from knowledge external to local knowledge (H4). However, the estimated coefficients associated with IS2 and IS3 are insignificant when in the growth rate dimension, and the size of the estimates are only slightly different than the reference group across the three columns with different innovation indicators.
We turn to examining the prediction that the growth rate of exporters with persistent innovation engagement is always larger than the growth rate of other exporting firms, irrespective of location (H5). The results for the three different innovation indicators clearly show that the hypothesis cannot be rejected. Moreover, the size of the estimates indicates a process of divergence and increased heterogeneity between exporters with recurrent innovation efforts and other exporters. Assuming an annual TFP growth rate of 3.0 per cent as the base value for productivity growth over the 1997–2008 period for the representative non-persistent innovative exporter in our data, the annual growth rate is 0.1–0.7 per cent higher for persistent innovative exporters. The difference between the two categories of firms is smallest when we define innovation by firms’ recurrent presence in the export market year after year and when innovators are in locations with less access to potential external knowledge (column 1). The estimated coefficient of 0.207 for a patenting exporter in knowledge-intensive milieus (column 3, IS6) corresponds to a 0.7 per cent higher annual growth rate than non-persistent innovative exporters.

Our final prediction is that among PI-exporting firms, those located in environments with the best access to external knowledge will have the fastest TFP growth (H6). Table 4 shows that the growth rate for persistent innovators correlates positively with external knowledge intensity, which confirms our a priori assumption. The spillover effect corresponds to 0.2 per cent when comparing localisation in the poorest (IS4) and richest (IS6) external knowledge milieus, when innovation is proxied by the capacity to launch new products in foreign markets. The equivalent difference for patenting firms is 0.4 per cent.

The point estimates for the control variables are remarkably homogenous across the three regression results presented in Table 4. Notably, the growth rate of TFP is a positive function of export experience, which offers some support for the presence of learning by exporting. Moreover, the results show that the growth rate is significantly higher for domestically owned multinationals (OW3) and foreign multinationals (OW4) compared with independent domestic firms (OW1) and domestic groups (OW2). The test statistics for the GMM model are satisfying across the growth regressions.

Overall, the results in Tables 3 and 4 allow us to draw three conclusions about the determinants of the firm’s decisions regarding innovation and location. First, a favourable location influences productivity for both a persistently innovative exporting firm and other exporters. Firms in knowledge-intensive milieus have a significantly higher level of productivity than firms in locations with less access to external knowledge. The effect of location is further reinforced by the choice of conducting innovation persistently. Second, we see no growth impact of the external knowledge pool among firms that are not innovating persistently. Third, a history of prior investment in innovation activities leads to substantially higher growth rates. Fourth, the TFP growth rate among persistently innovative exporters increases with the size of the external pool of knowledge. The cumulative effect of the difference in growth between persistent innovative exporters and other exporters leads to increased heterogeneity between the two categories of firms.

c. Comparison of Level and Growth Rate Estimates

A remaining issue concerns the differences in relation to IS variables between estimations using equation (4), which estimates log productivity, and equation (5), which considers productivity growth. While we predicted that a persistently innovative exporting firm will always be more productive and grow faster than non-persistent innovators, regardless of location, this
was consistently confirmed only in the growth dimension. The level equation produced mixed results. How can this be explained?

Let us take a closer look at the IS estimates in Table 3 and the Wald test of equality of means in the lower portion of the table. First, it should be noted that persistent innovators (IS6) in knowledge-intense milieus are always more productive than NPI exporters in all types of locations, regardless of which of the three alternative innovation measures we use (see row 6). Second, persistent innovators (IS5) in locations with a medium level of access to external knowledge are always significantly more productive than NPI exporters when innovation is proxied by patents (row 5, column 3). Third, the results in column 2 show that the IS5 estimates for persistent innovators measured by the introduction of new exports are always larger than the coefficients for NPI exporters; however, the productivity difference is significant only when the IS5 variable is compared with the IS1 and IS2 variables. Comparing IS5 with IS3 (non-persistent innovators in high-access locations), the estimates are 0.037 and 0.025, respectively, and the Wald test cannot reject that the means are equal. When innovation is defined as export persistency, the IS5 results are not significantly larger than the IS1-IS3 estimates (see column 1). Thus, if we ignore the IS5 and export persistency, which can be regarded as our weakest innovation indicator, the main difference between Tables 3 and 4 concerns the IS4 variable.

Our tentative explanation of why persistent innovative exporters in less knowledge-dense regional environments do not have a higher level of productivity than other exporters in local environments with both low, medium and high levels of access to external knowledge concerns collective learning. The creation and development of a localised knowledge base can be shared among firms and individuals through both conscious and unconscious mechanisms as well as both pecuniary and non-pecuniary knowledge exchanges, such as the ‘best practice solutions’ of labour mobility, manager mobility, board members, entrepreneurial spin-offs from existing firms, research collaborations, knowledge-intensive service producers and local universities (for a detailed discussion, see Keeble and Wilkinson, 1999). If the local knowledge base is limited, its leverage effect on firms’ internal knowledge may be small for both recurrent innovators and other firms. This in turn impedes the static effect on the firms’ productivity level (hampering the Solow convergence). At the same time, innovative companies in general and persistent innovative companies in particular are more inclined to continuously absorb new ideas from a more global environment, which could have an impact on the dynamic of productivity even for companies in geographically unfavourable environments. In our study, these two opposite factors could explain the divergent results for the IS4 variable shown in Tables 3 and 4.

6. CONCLUSIONS

This paper investigates whether exporting firms enjoy higher levels and growth rates of productivity depending on the persistency of their own knowledge-generating activities and their access to potential knowledge outside the firm. One of the novel contributions of this study is its attempt to jointly evaluate the impact on productivity of both firm innovation and the knowledge intensity of the municipality.

We estimate dynamic GMM models that capture the elasticities of both productivity and growth with respect to the long-run innovation strategy of firms and their particular locations, controlling for productivity and growth in previous periods as well as for firm size, export experience, ownership structure, industry classification, external shocks and unobserved firm

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heterogeneity. To assess the joint impact of internal knowledge and external knowledge, we use firm data collected from Swedish manufacturing industry from 1997 to 2008. The unbalanced panel consists of 9,580 firms with 10 employees or more and includes the entire population of firms in this category.

While previous studies have documented large heterogeneity in performance among exporters, we show that this may be related to both innovation and location.

Overall, the results in Tables 3 and 4 allow us to draw three conclusions about the determinants of the firm’s decisions regarding innovation and location. First, a favourable location influences productivity for both persistently innovative exporting firms and other exporters. Firms in knowledge-intensive milieus have a significantly higher level of productivity than firms in locations with less access to external knowledge. The effect of location is further reinforced by the choice to conduct innovation persistently. Second, we see no impact of the growth of the external knowledge pool among firms that do not innovate persistently. Third, a history of prior investment in innovation activities leads to substantially higher growth rates. Fourth, the TFP growth rate among persistent innovative exporters increases with the size of the external pool of knowledge. The cumulative effect of the difference in growth between persistently innovative exporters and other exporters leads to increased heterogeneity between the two categories of firms.

REFERENCES


APPENDIX

TABLE A1
Producer Services with More Than 30 per cent Knowledge Intensity in 2007

<table>
<thead>
<tr>
<th>SIC 2002</th>
<th>Industry</th>
<th>Knowledge Intensity, %</th>
<th>Fraction of KIPS 30</th>
</tr>
</thead>
<tbody>
<tr>
<td>7220</td>
<td>Software consultancy and supply</td>
<td>46.1</td>
<td>18.45</td>
</tr>
<tr>
<td>74202</td>
<td>Construction and other engineering activities</td>
<td>38.4</td>
<td>16.84</td>
</tr>
<tr>
<td>65120</td>
<td>Monetary intermediation</td>
<td>32.5</td>
<td>12.28</td>
</tr>
<tr>
<td>74140</td>
<td>Business and management activities</td>
<td>45.2</td>
<td>11.16</td>
</tr>
<tr>
<td>74120</td>
<td>Accounting, book-keeping and auditing activities: tax consultancy</td>
<td>41.2</td>
<td>7.71</td>
</tr>
<tr>
<td>72210</td>
<td>Publishing of software</td>
<td>50.3</td>
<td>5.13</td>
</tr>
<tr>
<td>74501</td>
<td>Labour recruitment activities</td>
<td>35.9</td>
<td>3.98</td>
</tr>
<tr>
<td>73102</td>
<td>R&amp;D in engineering and technology</td>
<td>68.5</td>
<td>3.15</td>
</tr>
<tr>
<td>74111</td>
<td>Legal advisory</td>
<td>70.9</td>
<td>2.45</td>
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<tr>
<td>74850</td>
<td>Secretarial and translation activities</td>
<td>32.9</td>
<td>2.00</td>
</tr>
<tr>
<td>65220</td>
<td>Credit granting</td>
<td>31.7</td>
<td>1.90</td>
</tr>
<tr>
<td>61102</td>
<td>Sea and coastal water transport</td>
<td>42.8</td>
<td>1.90</td>
</tr>
<tr>
<td>74201</td>
<td>Architectural activities</td>
<td>67.1</td>
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</tr>
<tr>
<td>73103</td>
<td>R&amp;D in medical and pharmaceutical science</td>
<td>69.7</td>
<td>1.50</td>
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<tr>
<td>73101</td>
<td>R&amp;D in natural science</td>
<td>74.3</td>
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<td>74104</td>
<td>R&amp;D in agricultural science</td>
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<tr>
<td>74130</td>
<td>Market research and public opinion pulling</td>
<td>36.1</td>
<td>0.87</td>
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<td>74872</td>
<td>Design activities</td>
<td>32.4</td>
<td>0.86</td>
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<td>67120</td>
<td>Security broking and fund management</td>
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<td>Life insurance</td>
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<td>0.79</td>
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<td>67202</td>
<td>Activities auxiliary to insurance and pension funding</td>
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<td>Database activities</td>
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<td>65232</td>
<td>Unit trust activities</td>
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<td>Investment trust activities</td>
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<td>Advisory activities concerning patents and copyrights</td>
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<td>73202</td>
<td>R&amp;D in humanities</td>
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<td>74150</td>
<td>Management activities of holding companies</td>
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<td>67110</td>
<td>Administration of financial markets</td>
<td>48.6</td>
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</tr>
<tr>
<td>65110</td>
<td>Central banking</td>
<td>54.0</td>
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</tr>
<tr>
<td>66020</td>
<td>Pension funding</td>
<td>40.6</td>
<td>0.09</td>
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<td>73105</td>
<td>Interdisciplinary R&amp;D in natural science and engineering</td>
<td>69.9</td>
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<td>65210</td>
<td>Financial leasing</td>
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<tr>
<td>73201</td>
<td>Interdisciplinary R&amp;D in humanities and social science</td>
<td>77.8</td>
<td>0.04</td>
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<tr>
<td>70110</td>
<td>Development and sales of real estate</td>
<td>40.5</td>
<td>0.02</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Innovation indicator</td>
<td>1 Firms that engaged in export activities in all years</td>
</tr>
<tr>
<td></td>
<td>2 Firms that have introduced two or more new exported products during this period</td>
</tr>
<tr>
<td></td>
<td>3 Firms that have applied for patents at least two years during this 12-year period</td>
</tr>
<tr>
<td>External knowledge</td>
<td>Level of access to knowledge-intensive producer services, divided into three groups: low, medium, high</td>
</tr>
<tr>
<td>Level, log TFP</td>
<td>Level of TFP as a measure of firm productivity. TFP is computed as the residual of the Cobb-Douglas production function based on the method introduced by Levinsohn and Petrin (2003)</td>
</tr>
<tr>
<td>Growth, log TFP</td>
<td>Growth of log TFP</td>
</tr>
<tr>
<td>EMP</td>
<td>Number of employees in each firm</td>
</tr>
<tr>
<td>Growth, EMP</td>
<td>Employment growth</td>
</tr>
<tr>
<td>PC, log</td>
<td>Log of physical capital</td>
</tr>
<tr>
<td>HC</td>
<td>Share of employees with at least three years of university education</td>
</tr>
<tr>
<td>EE</td>
<td>Export experience, number of years in the export market</td>
</tr>
<tr>
<td>OW1</td>
<td>Domestic non-affiliate enterprises</td>
</tr>
<tr>
<td>OW2</td>
<td>Domestic group enterprises</td>
</tr>
<tr>
<td>OW3</td>
<td>Domestic multinational enterprises</td>
</tr>
<tr>
<td>OW4</td>
<td>Foreign multinational enterprises</td>
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</tbody>
</table>
Paper III
Survival, productivity and growth of new ventures across locations

Hans Lööf · Pardis Nabavi

1 Introduction

Entrepreneurship is recognized as an engine of economic dynamics, and start-ups by ex-employees of incumbent firms are found to be a distinctive class of new firms (Agarwal et al. 2004; Klepper and Sleeper 2005; Andersson et al. 2012). However, a new company is not just affected by inherited experience from other companies via entrepreneurial spawning. Experience and knowledge of technical and organizational solutions, markets, and other factors can also spill over from the geographical environment in the form of industrial clusters, agglomerations, labor mobility and proximity to dominant customers. A large body of literature has examined how aggregate knowledge sources inside a region generate spillovers and affect the outcome of firms located in a region (e.g., Jaffe 1986; Audretsch and Feldman 2004). Despite a large interest in both performance of new firm formations and the spatial importance of new ventures, there are remarkably few systematic studies on both these factors within the same framework. Our primary contribution is a unique systematic comparison of the survival, productivity and growth of spinoffs and other new firms in different geographical locations. Most previous studies have used samples of new firms or new firms in a specific industry, while our study is based on population data and covers the entire economy except for the primary sector. We study approximately 23,000 Swedish ex-employee start-ups and genuinely new entrants (GNE) in metro-cities,
Location-specific benefits can differ both between manufacturing and services and between knowledge-intensive production and other specialties. Therefore, we analyze new firm formation across regions in two categories of manufacturing with distinctly different technology intensities, and two categories of services with distinctly different knowledge intensities. The rich data set allows us to follow the companies throughout the entire critical first five-year period in the market.

In the econometric analysis, we first apply a discrete-time hazard model to study survival. Then, a dynamic panel data approach is used to assess productivity and growth. The paper establishes the following regularities. First, spinoffs in services have a significantly higher survival rate than other new ventures, wherever they are located. Among manufacturing firms, only spinoffs outside metro areas are more prone to survive the first 5 years than genuinely new entrants. Second, in services, spinoffs are more productive than other new ventures across all regions. Manufacturing spinoffs in metro-cities have a superior productivity to that of other new firms in the same sector. Third, we find that both spinoffs and other new businesses benefit from presence in metro-cities in terms of productivity growth, regardless of their knowledge intensity. Concerning manufacturing, new firms linked to a father firm do not differ in productivity growth compared to other new manufacturers. Concerning services, the results for employment growth among new firms are mixed.

The rest of this paper is organized as follows. Section 2 provides a brief literature review, Sect. 3 provides data and Sect. 4 provides the model. The results are reported in Sect. 5, and Sect. 6 concludes the paper.

2 Previous literature

Mansfield (1962) was one of the first to study new firms’ entry processes and their determinants in a systematic way, while Dosi (1988), in contrast to the neoclassical view, discussed the microeconomic variety characterizing new entrants. Jovanovic (1982) represents the earliest attempt to formally model the post-entry evolution of new entrants. The noisy selection model predicts that only efficient firms survive and grow.

More recent research tries to incorporate the space with the analysis. Acs et al. (2007) suggest that the conditions for survival, productivity and growth of heterogeneous newborn firms vary not only with firm- and industry-specific factors but also with location attributes. Regional variations in both survival and survivors’ performances might be correlated with particular industry factors such as knowledge and technology intensity (Brixy and Grotz 2007), industry clusters (Saxenian 1994), and a variety of firm-specific factors such as close attachment to a previous employer, managerial capacity and human capital.¹

Recent research has documented several regularities in new firm formation with potential impact on firms’ futures. About two out of three new founders come from the same region and the same sector as their previous employment or business activity, while the remainders are in migrating entrepreneurs or young people with no previous job experience (Shane 2000; Renski 2009). People with experience from incumbent firms, people who start a new firm in the same sector and the same region as the parent firm or previous employers are more likely to be successful than leaders of other new firms (Storey 1994; Klepper 2002; Andersson et al. 2012). New firms created by locals are bigger, more valuable and better financed than startups created by non-locals (Michelacci and Silva 2005).

It has also been shown that human capital and specific rather than generic education and skills in economic, managerial, technical and scientific fields increase both the likelihood of survival and the economic performance of new firms (Brüderl et al. 1992; Almus and Nerlinger 1999; Colombo and Grilli 2005).

The primary motivation to start a new venture has been found to be a predictor of post-entry profitability and growth. The research differs between dynamic factors such as new innovative ideas and more defensive factors such as escape from unemployment (see Vivarelli and Audretsch 1998; Arrighetti and Vivarelli 1999; Andersson and Klepper 2013). The literature suggests that the risk of unemployment and similar motivations for starting a new business are

¹ Wennberg and Lindqvist (2010) find a positive effect of localization, in the form of high concentration of related workers and establishments, on the survival of Swedish entrants in knowledge-intensive industries.
associated with higher death risk and lower productivity (Pfeiffer and Reize 2000; Andersson and Wadensjö 2006). Because dynamic factors are more frequent in agglomeration areas, the underlying motivation will influence interregional variations in new business survival and growth.

However, few studies have systematically examined geographical variation in survival, productivity and growth among new businesses. One main reason is lack of suitable micro data. In fact, very few countries have databases that allow for creating matched employer–employee data that is suitable for the systematic examination of spatial variations in new firm entry, survival and performance. The three Nordic countries, Denmark, Norway and Sweden, are among the few countries where such studies are possible. Portugal and Brazil have similar data, while studies in other countries are performed using second-best data solutions.

Typically, existing studies on interregional variation in the viability of new ventures build on cross-sectional samples or panel data on selected geographical areas, preferably metropolitan economies. Most studies have not been able to confirm the prediction by Hoover and Vernon (1959) that central locations are advantageous for new businesses. See, for instance, Audretsch and Fritsch (1994), Keeble and Walker (1994), Reynolds (1994), Reynolds et al. (1995), Fotopoulos and Spence (1998), Armington and Acs (2002), Rosenthal and Strange (2003), Lee et al. (2004), Fritsch and Mueller (2005) and Feser et al. (2008).

The justifications for rejecting the Hoover and Vernon hypothesis include the following: (1) new firms that compete through innovation have a higher risk of failure, and because this type of firm is disproportionately located in the core, large cities will have higher rates of failure than less dense areas (Renski 2009); (2) complex, sticky and tacit knowledge spillovers are believed to be strongly dependent on proximity (Greenstone et al. 2010; Lychagin et al. 2010), but these spillovers will benefit knowledge-intensive businesses more than other startups (Campi et al. 2004); and (3) firms entering in the metropolitan fringe may benefit from the size and density of the nearby area without incurring the same costs (Phelps 2004). Some studies are able to establish a positive link between new firm formation and population size. Grek et al. (2009) show that the market potential as measured by local and external accessibility to gross regional product has a strong, significant impact on the entry of new firms. (See also Hoogstra and van Dijk 2004; Gabe 2005). Some studies indicate that spinoffs are more prone to take advantage of agglomerations than other firms (see, for instance, Nicolaou and Birley 2003; Acs et al. 2009).

The existing study most similar to ours is Renski (2009), which examines variation in entry, survival and growth inside and outside metro areas in the US. Renski finds that new knowledge-intensive firms in central cities have higher failure rates but that employment growth is faster than at corresponding firms in other places. The study also reports that suburbs, small cities and rural segments of metropolitan cities tend to be good incubators for new entering firms. However, no local milieu favors entrepreneurship across all sectors and performance measures.

3 Data and variables

The firm-level data used in this study were originally constructed from audited register information on firm characteristics based on annual reports on firms in Sweden provided by Statistic Sweden (SCB). Based on both firm- and individual-level data, the new firms are classified into two different categories: employee-startups and genuinely new ventures, which are not directly tied to any existing firms through employment migration.

Following Andersson and Klepper (2013), employee startups are recognized by observing the presence of ex-employees at both the parent company and the new firm. The method begins by identifying whether the majority of people in a new firm in a particular year were also a minority in another firm during the previous year.2 If the parent firm continues to exist in the year of the new firm’s founding, and if the new firm is not a result of a merger, then the start-up firm is considered a spinoff.3

2 Firms that were a minority in the parent firm the year before the transition to the new venture but a majority in the new firm the year after the transition are considered to be entrepreneurial spawns or spinouts.

3 To be considered a spinout, the new venture cannot be a branch of an existing business. Some firms may erroneously be classified as new if they have been inactive for some time or if they have high turnover. By applying two identifiers coming from Business Statistic and Statistic Sweden and by tracking each firm during the years prior to their entry (our records date back to 1997), we avoid misclassifying these firms as new.
If the employees of the new firm were unemployed the previous year, or the majority of employees were not working in a specific firm, these new firms are classified as genuinely new ventures. All new firms with over ten employees during the first year of operation are dropped to restrict the sample to independent new firms and to avoid capturing the probable effect of outsourcing and mergers and acquisitions. Moreover, new firms with one employee (self-employers) are also omitted from the sample.

Our main focus is on the cohorts of new firms founded during the period 2000–2004, and the window of observation is the period 2000–2008. We are thus able to follow the development of each of the new firms for 5 years after their entry.4 In our data, we observe a total of 5,195 unique entrants spawned by incumbent firms over the period 2000–2004 and 17,842 genuine new firms. In the first part of the analysis, we use all of the approximately 103,000 observations on these firms to estimate the likelihood of survival in the first 5 years on the market. The second part of our study considers growth performance, and following the tradition started with Audretsch (1995), the sole focus is on survived firms. In total, 2,095 spinoffs and 5,629 genuinely new firms remained active 5 years after entry.

In the analysis, we separate the basic sample into four subsamples: firms specializing in high and high-medium manufacturing technology, low and low-medium manufacturing technology, knowledge-intensive services and less knowledge-intensive services. The motivation is that a variety of fields in the literature on entrepreneurship, economics of innovation and economic geography explain advantages of firm location with factors such as natural advantages due to path dependency, pecuniary economics related to transportation cost and scale economics, proximity to consumers, suppliers and competitors, access to specialized inputs and specialized workers, technological spillovers and other externalities (this literature includes Marshall 1920; Porter 1990; Krugman 1991; Krugman and Venables 1995; Fujita and Thisse 2002; Acs and Armington 2004; Iammarino 2005; Lychagin et al. 2010). Location-specific benefits differ between both manufacturing and services and between knowledge-intensive production and other specialties.

We distinguish between four types of locations of the new firms: “metro cities”, “metro regions”, “urban areas” and “rural areas”. Sweden’s three metropolitan cities, Stockholm, Gothenburg and Malmö, are classified as metro cities. Metro regions include municipalities where 100% of the population live within cities (except for Stockholm, Gothenburg and Malmö) or within a 30 km distance from these cities. Municipalities with a population of at least 30,000 inhabitants and where the largest city has a population of 25,000 people or more are classified as urban areas. The remainder of the municipalities composes the final category of rural areas. “Metro cities” represent 17% of the Swedish population. “Metro regions”, “urban areas” and “rural areas” represent 18, 30 and 35% of the population, respectively.

The distribution of spinoffs and genuinely new firms across industries and regions is displayed in Table 1. The two largest categories of start-ups are knowledge-intensive services and less knowledge-intensive services. Approximately 1 out of 5 new firms may be considered spinoffs.

Renski (2009) argues that more highly populated areas may be expected to have a larger pool of potential entrepreneurs. However, in accordance with the discussion above, the particular geographical benefit available to a new firm varies with both firm characteristics and industry-specific issues. In Table 1, we calculate a location quotient (LQ), which shows the relative entrepreneurial frequency of a particular region. Therefore, the LQ value equals one when an area type contains a share of all new firms that is equal to the area type’s share of the total population. The table reports that new knowledge-intensive services are overrepresented in metro cities, whereas a disproportionately large number of start-ups in low technology manufacturing are located in less populated areas. Because new entrepreneurs tend to remain close to their geographical origin (Costa and Baptista 2012), we are not surprised that the LQ is almost the same for both genuinely new entrepreneurs and spinoffs from established firms.

Previous literature has shown that start-ups linked to incumbent firms belong to a specific type of new firm formation in terms of productivity and

---

5 Primary sector is not included in the study. For a detailed description of the classification, see http://epp.eurostat.ec.europa.eu/cache/ITY_SDDS/Annexes/hrst_st_esms_an9.pdf.
Typically, this literature does not consider the relevance of geography. In this paper, we focus on several aspects of new firm formation: the capacity to survive and surviving firms’ capacity to create productivity and growth. The dependent variable in the first part of the study is the duration that a firm remains in the business. The three other dependent variables are the log of value added, the growth of value added and the growth of labor in each period of time.

The key explanatory variables used in this study are interaction variables between location dummies and types of new firms. The reference group in all the regressions comprises genuinely new firms located in “rural areas”.

Our control variables are related to the characteristics of firms. We control for the level of the human capital of new ventures, expressed as the fraction of employees with at least 3 years of university education, physical capital, measured as log annual investment in machineries, size, which is measured as the log value of the number of employees, and ownership, which distinguishes between non-affiliate and members of a domestic group, a domestic multinational group and a foreign multinational group. We also control for the particular 2-digit industry to which the new firms belong. All parametric regressions include year dummies. In the growth regressions, we also control for time-invariant non-observed heterogeneity.

Tables 2 and 3 report descriptive statistics for manufacturing and service firms. The left section of the tables presents statistics for genuinely new firms, and the right section presents statistics for spinoffs. Both tables show that spinoffs on average are larger in size and have higher value added than other start-ups for each of the four locations. However, no systematic difference in the growth of value added or labor between the two categories of firm is found. The intensity of human capital differs across locations but not between spinoffs and genuinely new entrants.
Representing the only exception are knowledge-intensive services in metro cities. In this case, the typical spinoffs have somewhat higher fraction of university-educated employees than other firms. Notable is the high level of failure among new firms, and the difference between GNE and spinoffs. In the whole sample, only 35% of new entrants with 2–10 employees survived the first 5 years on the market. The descriptive statistics show that ex-employees are substantially more likely to survive.

4 Methodology

Two different econometric techniques are implemented to test the hypotheses on the optimal locations of new ventures. To analyze the life duration of new firms, we adopt a proportional hazard approach allowing for discrete time intervals. The model used is a complementary log–log model that also controls for unobserved individual effects (Jenkins 2004). Our second approach is a dynamic model testing the causal relationship between location and growth.

Our hazard function estimation is

$$ \lambda_{it} = 1 - \exp(-\exp(\alpha(t) + \beta x_{it} + u_{it})) $$

(1)

where $\lambda_{it}$ is the failure rate of a new firm $i$ at time $t$, $\alpha(t)$ is the baseline failure rate as a function of time, and $\beta$ is a vector of parameters measuring the influence of explanatory variables (x) on the baseline failure rate. We assume that $u_{it}$ is the normally distributed error with zero mean.

The general growth model is a standard Cobb–Douglas production function. The data are repeated measurements at different points in time for the same firms. The variables we would like to explain are productivity growth and employment growth. The key interest is to determine the elasticity of productivity and growth and employment growth with respect to different locations. Specified in

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Genuinely new ventures</th>
<th>Spinoffs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Metro cities</td>
<td>Metro regions</td>
</tr>
<tr>
<td>Survival</td>
<td>0.28</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td>(1.14)</td>
<td>(1.01)</td>
</tr>
<tr>
<td></td>
<td>(0.87)</td>
<td>(0.72)</td>
</tr>
<tr>
<td>Emp. growth (%)</td>
<td>15.64</td>
<td>13.54</td>
</tr>
<tr>
<td></td>
<td>(0.46)</td>
<td>(0.43)</td>
</tr>
<tr>
<td>Human capital</td>
<td>0.16</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
<td>(0.19)</td>
</tr>
<tr>
<td>Phys capital</td>
<td>11.43</td>
<td>11.31</td>
</tr>
<tr>
<td></td>
<td>(2.87)</td>
<td>(3.23)</td>
</tr>
<tr>
<td>Emp. log</td>
<td>1.1</td>
<td>0.96</td>
</tr>
<tr>
<td></td>
<td>(0.84)</td>
<td>(0.77)</td>
</tr>
<tr>
<td>Domestic group</td>
<td>0.79</td>
<td>0.89</td>
</tr>
<tr>
<td>Foreign MNE</td>
<td>0.06</td>
<td>0.02</td>
</tr>
<tr>
<td>Domestic MNE</td>
<td>0.03</td>
<td>0.02</td>
</tr>
<tr>
<td>Domestic indep.</td>
<td>0.12</td>
<td>0.07</td>
</tr>
<tr>
<td>No. observations</td>
<td>1,279</td>
<td>722</td>
</tr>
<tr>
<td>Unique firms</td>
<td>273</td>
<td>145</td>
</tr>
</tbody>
</table>

Mean values and standard deviations (SDs)
logarithmic transformation, the basic model may be expressed as follows:

$$y_{it} = \alpha_i + \alpha_j + \gamma_1 y_{i,t-n} + \rho_1 LGNV_{it} + \rho_2 LSO_{it}$$
$$+ \rho_3 EMP_{i,t-n} + \rho_4 PC_{i,t-n} + \rho_5 HC_{i,t}$$
$$+ \rho_6 OW_{it} + \varepsilon_{it}$$

(2)

$$\Delta y_{it} = \alpha_i + \alpha_j + \gamma_1 y_{i,t-n} + \rho_1 LGNE_{it}$$
$$+ \rho_2 LSO_{it} + \rho_3 \Delta EMP_{i,t-n} + \rho_4 \Delta PC_{i,t-n}$$
$$+ \rho_5 HC_{i,t} + \rho_6 OW_{it} + \varepsilon_{it}$$

(3)

where $y_{it}$ is the log productivity of firm $i$ in year $t$, $\alpha_i$, $\alpha_j$ and $\gamma_1$ are controls for fixed effects (firm-specific, industry-specific and time-specific, respectively), $y_{i,t-n}$ is lagged log productivity, LGNE refers to interaction dummies between four different locations and GNEs, LSO is a similar interaction variable between location and spinoffs, EMP and PC are the log values of employment and physical capital, respectively, HC is the fraction of employees with at least 3 years of university education, OW represents corporate ownership categorical dummies and $\varepsilon$ is the idiosyncratic error term. The EMP variable is omitted in the employment growth regression. In this regression, the dependent variable $y_{it}$ in Eq. (3) is labor.

The empirical model that we apply is a dynamic one-step system GMM estimator (Arellano and Bover 1995; Blundell and Bond 1998). To estimate Eqs. 2 and 3, we must classify the variables as endogenous, predetermined, weakly exogenous and strictly exogenous. Based on the literature, we treat the determinants of productivity, human capital, physical capital and firm size (employment) as endogenous regressors. The endogeneity concern reflects the possible correlation between these variables and unobserved productivity shocks.

Our location interaction dummies and all the other dummy variables are all treated as exogenous in the model. It should be noted that the variation over time in LGNE and LSO is almost zero, as most firms do not change their location during the 5-year observation period. Finding a plausible instrument for this almost
constant variable is not possible in the present application (for a similar case, see Lychagin et al. 2010).

5 Results

In this section, we present the results of the survival analysis and the performance regressions. Table 4 reports the survival estimates for all new firms created between 2000 and 2004, whereas Tables 5, 6 and 7 present performance results in terms of labor productivity and growth rates of productivity and employment during the first 5 years of operations for surviving firms. Each of the tables presents results from four different regressions: (1) high and medium–high manufacturing technology, (2) low and medium–low manufacturing technology, (3) knowledge-intensive services and, (4) less knowledge-intensive services.

5.1 Survival of new firms

We begin the empirical analysis by considering the survival estimations in Table 4. It should be noted that non-survival is not always a failure. In some cases, companies have disappeared from the market due to acquisition. However, for the vast majority of businesses, shutting down is the result of weak performance.

The table reports the hazard rate, which is the likelihood that a new entrant will fail at a specific point in time, given that it has survived up to that point. Composing the reference group are genuinely new ventures in rural areas.

Table 4 Hazard ratios that new firms will fail for area types, by sectors and technological intensity

<table>
<thead>
<tr>
<th>Firm type by location</th>
<th>Manufacturing</th>
<th>Services</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>High and medium high-tech</td>
<td>Medium–low and low-tech</td>
</tr>
<tr>
<td>Metro cities&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.967 (0.195)</td>
<td>1.230** (0.113)</td>
</tr>
<tr>
<td>Metro regions&lt;sup&gt;a&lt;/sup&gt;</td>
<td>1.057 (0.227)</td>
<td>1.096 (0.123)</td>
</tr>
<tr>
<td>Urban areas&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.877 (0.164)</td>
<td>1.032 (0.087)</td>
</tr>
<tr>
<td>Spinoffs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Metro cities</td>
<td>0.862 (0.238)</td>
<td>0.773 (0.128)</td>
</tr>
<tr>
<td>Metro regions</td>
<td>0.516* (0.193)</td>
<td>0.770 (0.174)</td>
</tr>
<tr>
<td>Urban areas</td>
<td>0.253*** (0.095)</td>
<td>0.623*** (0.106)</td>
</tr>
<tr>
<td>Rural areas</td>
<td>0.437*** (0.108)</td>
<td>0.698*** (0.082)</td>
</tr>
<tr>
<td>Emp, log</td>
<td>0.827** (0.067)</td>
<td>0.750*** (0.030)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,986</td>
<td>7,123</td>
</tr>
<tr>
<td>Unique firms</td>
<td>631</td>
<td>2,375</td>
</tr>
</tbody>
</table>

Hazard ratio >1 decreases the likelihood of survival. A hazard ratio <1 increases the likelihood of survival.

S.Es in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

<sup>a</sup> Reference is genuinely new entrants in rural areas.
Table 5  Dependent variable: level of value added, GMM

<table>
<thead>
<tr>
<th>Firm type by location</th>
<th>Manufacturing</th>
<th>Services</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>High and medium high-tech</td>
<td>Medium–low and low tech</td>
</tr>
<tr>
<td>Metro cities(^a)</td>
<td>0.076 (0.168)</td>
<td>0.012 (0.077)</td>
</tr>
<tr>
<td>Metro regions(^a)</td>
<td>−0.050 (0.108)</td>
<td>0.013 (0.059)</td>
</tr>
<tr>
<td>Urban areas(^a)</td>
<td>−0.011 (0.079)</td>
<td>0.036 (0.046)</td>
</tr>
</tbody>
</table>

**Spinoffs**

<table>
<thead>
<tr>
<th>Firm type by location</th>
<th>Manufacturing</th>
<th>Services</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>High and medium high-tech</td>
<td>Medium–low and low tech</td>
</tr>
<tr>
<td>Metro cities</td>
<td>0.329*** (0.139)</td>
<td>0.209** (0.098)</td>
</tr>
<tr>
<td>Metro regions</td>
<td>0.116 (0.145)</td>
<td>−0.067 (0.087)</td>
</tr>
<tr>
<td>Urban areas</td>
<td>0.108 (0.106)</td>
<td>0.060 (0.061)</td>
</tr>
<tr>
<td>Rural areas</td>
<td>0.061 (0.098)</td>
<td>0.034 (0.043)</td>
</tr>
<tr>
<td>Emp, log</td>
<td>0.405 (0.258)</td>
<td>1.204*** (0.165)</td>
</tr>
<tr>
<td>Human capital</td>
<td>0.121 (0.651)</td>
<td>−0.322 (0.389)</td>
</tr>
<tr>
<td>Phys capital</td>
<td>−0.021 (0.041)</td>
<td>−0.009 (0.030)</td>
</tr>
<tr>
<td>Dom MNE(^b)</td>
<td>0.145 (0.202)</td>
<td>0.267 (0.194)</td>
</tr>
<tr>
<td>For MNE(^b)</td>
<td>0.285* (0.157)</td>
<td>0.073 (0.189)</td>
</tr>
<tr>
<td>DOM indep.(^b)</td>
<td>−0.050 (0.090)</td>
<td>−0.143*** (0.059)</td>
</tr>
<tr>
<td>Observations</td>
<td>814 (222)</td>
<td>2,686 (712)</td>
</tr>
<tr>
<td>Unique firms</td>
<td>222 (712)</td>
<td>712 (2,274)</td>
</tr>
<tr>
<td>AR (2)</td>
<td>0.972 (0.423)</td>
<td>0.392 (0.886)</td>
</tr>
<tr>
<td>Hansen overid</td>
<td>0.423 (69)</td>
<td>0.886 (94)</td>
</tr>
<tr>
<td>Instruments</td>
<td>69 (36)</td>
<td>66 (34)</td>
</tr>
<tr>
<td>Lag limits</td>
<td>(3 3)</td>
<td>(3 2)</td>
</tr>
</tbody>
</table>

Covariates included: human capital, physical capital, firm size, corporate ownership structures, industry dummies and year dummies
SEs in parentheses *** \( p < 0.01, ** \( p < 0.05, * \( p < 0.1

\(^a\) Reference is genuinely new entrants in rural areas

\(^b\) Reference is domestic firms belonging to a uninational domestic group

To interpret Table 4, consider the first column, which presents the results for manufacturing firms in high and medium–high manufacturing. The first row in this column contains the correlation coefficient for the difference between the reference group and GNEs in metro cities. Estimates lower than unity correspond to a higher survival rate than the reference, and estimates larger than unity correspond to a lower
Table 6  Dependent variable: growth rate of value added, GMM

<table>
<thead>
<tr>
<th>Firm type by location</th>
<th>Manufacturing</th>
<th>Services</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>High and medium high-tech</td>
<td>Medium–low and low tech</td>
</tr>
<tr>
<td>Metro cities(^a)</td>
<td>0.043</td>
<td>−0.018</td>
</tr>
<tr>
<td></td>
<td>(0.093)</td>
<td>(0.047)</td>
</tr>
<tr>
<td>Metro regions(^a)</td>
<td>−0.022</td>
<td>−0.044</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>Urban areas(^a)</td>
<td>−0.083</td>
<td>−0.016</td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Spinoffs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Metro cities</td>
<td>0.145</td>
<td>−0.040</td>
</tr>
<tr>
<td></td>
<td>(0.106)</td>
<td>(0.055)</td>
</tr>
<tr>
<td>Metro regions</td>
<td>0.069</td>
<td>−0.073</td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.062)</td>
</tr>
<tr>
<td>Urban areas</td>
<td>0.067</td>
<td>0.038</td>
</tr>
<tr>
<td></td>
<td>(0.058)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>Rural areas</td>
<td>0.037</td>
<td>0.024</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Emp growth</td>
<td>0.655***</td>
<td>0.655***</td>
</tr>
<tr>
<td></td>
<td>(0.226)</td>
<td>(0.155)</td>
</tr>
<tr>
<td>Human capital</td>
<td>−0.275</td>
<td>−0.159</td>
</tr>
<tr>
<td></td>
<td>(0.318)</td>
<td>(0.271)</td>
</tr>
<tr>
<td>Phys capital growth</td>
<td>0.028</td>
<td>−0.040</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Dom MNE(^b)</td>
<td>−0.072</td>
<td>0.190</td>
</tr>
<tr>
<td></td>
<td>(0.103)</td>
<td>(0.154)</td>
</tr>
<tr>
<td>For MNE(^b)</td>
<td>0.313***</td>
<td>0.229***</td>
</tr>
<tr>
<td></td>
<td>(0.146)</td>
<td>(0.112)</td>
</tr>
<tr>
<td>DOM indep.(^b)</td>
<td>−0.091</td>
<td>−0.107*</td>
</tr>
<tr>
<td></td>
<td>(0.058)</td>
<td>(0.059)</td>
</tr>
<tr>
<td>Observations</td>
<td>814</td>
<td>2,686</td>
</tr>
<tr>
<td>Unique firms</td>
<td>222</td>
<td>712</td>
</tr>
<tr>
<td>AR (2)</td>
<td>0.723</td>
<td>0.350</td>
</tr>
<tr>
<td>Hansen overid</td>
<td>0.365</td>
<td>0.215</td>
</tr>
<tr>
<td>Instruments</td>
<td>76</td>
<td>96</td>
</tr>
<tr>
<td>Lag limits</td>
<td>(1 1)</td>
<td>(2 1)</td>
</tr>
</tbody>
</table>

Covariates included: human capital, physical capital, firm size, corporate ownership structure, industry dummies and year dummies

SEs in parentheses *** \( p < 0.01 \), ** \( p < 0.05 \), * \( p < 0.1 \)

\(^a\) Reference is genuinely new entrants in rural areas

\(^b\) Reference is domestic firms belonging to a uninal national domestic group

survival rate than the reference. The estimate, 0.967, is close to unity and is not significantly different from the reference alternative. The second and third rows also report non-significant results. Rows 4–7 show the estimates for spinoffs (SO). The interpretations are as follows: technology-intensive SO-manufacturing firms outside metro areas are significantly more likely than all other new firms in this category to survive. The
Table 7  Dependent variable: growth of labor, GMM

<table>
<thead>
<tr>
<th>Firm type by location</th>
<th>Manufacturing</th>
<th>Services</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>High and medium high-tech</td>
<td>Medium–low and low tech</td>
</tr>
<tr>
<td>Metro cities\textsuperscript{a}</td>
<td>-0.067</td>
<td>-0.013</td>
</tr>
<tr>
<td>(0.076)</td>
<td>(0.040)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Metro regions\textsuperscript{a}</td>
<td>-0.086</td>
<td>-0.038</td>
</tr>
<tr>
<td>(0.073)</td>
<td>(0.047)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>Urban areas\textsuperscript{a}</td>
<td>0.022</td>
<td>-0.008</td>
</tr>
<tr>
<td>(0.056)</td>
<td>(0.029)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Spinoffs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Metro cities</td>
<td>0.071</td>
<td>-0.110\textsuperscript{**}</td>
</tr>
<tr>
<td>(0.092)</td>
<td>(0.048)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>Metro regions</td>
<td>-0.023</td>
<td>-0.095\textsuperscript{*}</td>
</tr>
<tr>
<td>(0.074)</td>
<td>(0.050)</td>
<td>(0.042)</td>
</tr>
<tr>
<td>Urban areas</td>
<td>0.025</td>
<td>-0.006</td>
</tr>
<tr>
<td>(0.049)</td>
<td>(0.038)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Rural areas</td>
<td>-0.061</td>
<td>-0.007</td>
</tr>
<tr>
<td>(0.051)</td>
<td>(0.030)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>Human capital</td>
<td>-0.111</td>
<td>-0.169</td>
</tr>
<tr>
<td>(0.260)</td>
<td>(0.201)</td>
<td>(0.088)</td>
</tr>
<tr>
<td>Phys capital growth</td>
<td>0.022</td>
<td>-0.020</td>
</tr>
<tr>
<td>(0.014)</td>
<td>(0.025)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Dom MNE\textsuperscript{b}</td>
<td>0.060</td>
<td>0.011</td>
</tr>
<tr>
<td>(0.133)</td>
<td>(0.082)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>For MNE\textsuperscript{b}</td>
<td>0.138\textsuperscript{*}</td>
<td>0.158\textsuperscript{*}</td>
</tr>
<tr>
<td>(0.082)</td>
<td>(0.083)</td>
<td>(0.041)</td>
</tr>
<tr>
<td>DOM indep.\textsuperscript{b}</td>
<td>0.060</td>
<td>-0.058\textsuperscript{*}</td>
</tr>
<tr>
<td>(0.046)</td>
<td>(0.033)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Observations</td>
<td>814</td>
<td>2,686</td>
</tr>
<tr>
<td>Unique firms</td>
<td>222</td>
<td>712</td>
</tr>
<tr>
<td>AR (2)</td>
<td>0.548</td>
<td>0.344</td>
</tr>
<tr>
<td>Hansen overid</td>
<td>0.149</td>
<td>0.128</td>
</tr>
<tr>
<td>Instruments</td>
<td>66</td>
<td>67</td>
</tr>
<tr>
<td>Lag limits</td>
<td>(1 1)</td>
<td>(1 1)</td>
</tr>
</tbody>
</table>

Covariates included: human capital, physical capital, firm size, corporate ownership structures, industry dummies and year dummies
SEs in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1
\textsuperscript{a} Reference is genuinely new entrants in rural areas
\textsuperscript{b} Reference is domestic firms belonging to a uninational domestic group

Point estimate for the average firm in a metro region outside a metro city is also significant, although only at the 10% level.

Continuing with medium–low and low technology manufacturing, column 2 indicates that starting a GNE in a metro city is a risky project. The likelihood of survival during the first 5 years is significantly lower compared to market entry in all other locations. With regard to spinoffs, the table reports that start-ups in urban and rural areas are most likely to survive.
The regression results for services show that GNEs in rural areas exhibit a significantly higher viability than GNEs in both high and less knowledge-intensive sectors. There are several not mutually exclusive interpretations. For instance, it might be a more significant step to start a service business in a rural area, as doing so requires a more detailed analysis of market conditions and the consequences of a failure. Alternatively, the competition is weaker and the firm might survive, even if the profitability is low. Spinoffs in the service sector are more prone to survive across all locations relative to the reference group, but the point estimates indicate that the likelihood of survival decreases with spatial proximity for both knowledge-intensive firms and less knowledge-intensive services.

5.2 Start-up productivity performance

Table 5 reports the first of three sets of production function estimates. The performance measure is log value added, controlling for firm size. Previous studies have shown that entrepreneurial ventures spawning from a father firm are superior to other types of newcomers in terms of profitability and productivity. Table 5 adds a spatial dimension to this literature. Looking across the four equations, we see a striking similarity between the two categories of manufacturing firms as well as between the two categories of service firms. The first two columns suggest that only ex-employee manufacturing start-ups in metro cities are more productive than new firms without any ties to a father firm. Spinoffs in other geographical areas are not more productive than other new firms, wherever they are located.

Moreover, we see that the average GNE specializing in high or low technology does not benefit from closeness to proximity areas and potential knowledge spillovers.

The main finding from the two service regressions is that spinoffs are always more productive than other new service ventures. In contrast to manufacturing, there is no metro city premium among either knowledge-intensive spinoffs or spinoffs in less knowledge-intensive service industries. In addition, similarly to manufacturing, we cannot establish any productivity difference between GNE across various locations.

The point estimates for the controls are quite heterogeneous across the table. The most robust results are that value added increases with firm size (not significant for high and medium–high technology firms) and that foreign-owned firms are more productive than domestic new entrants (not significant for low-medium and low technology manufacturing firms). Moreover, with locations controlled for, the results indicate that human capital is more important for services than other factors.

5.3 Growth rates

Table 6 presents the production function estimates for value-added growth. Considering the two manufacturing equations, we observe no significant differences in the estimates across locations or types of new firm formation. Spinoffs in metro cities are more productive than other new manufacturing firms, but their growth rates are not superior.

As shown in Table 6, estimates for services reveal several interesting results. First, GNEs in metro cities grow significantly faster in terms of value added than GNEs in areas with a lower population density. Second, there exists a premium for location in a metro-city among spinoffs in knowledge-intensive services. Third, for each type of location, spinoffs in both knowledge-intensive services and less knowledge-intensive services have faster growth rates than corresponding GNEs, although the difference is not significant in some cases.

Table 7 presents regression results for labor growth. Considering both high and medium–high technology manufacturing and knowledge-intensive services, no statistically significant differences in point estimates from the reference alternative are reported. Representing the only exception are knowledge-intensive service spinoffs in rural areas. Here the estimate is negative but only weakly significant. Somewhat surprisingly, the results suggest that spinoffs in low and medium–low manufacturing and located in metropolitan areas are growing more slowly in terms of labor than other firms in this category. Finally, Table 7 shows that both GNE and spinoffs in services with low knowledge intensity tend to grow at a higher rate if they are located in metro cities.

5.4 Test statistics

Our GMM results are sensitive to both the number of instruments, identification and serial correlation. The bottom sections of Tables 5, 6 and 7 report test
statistics on the validity of the regressions. First, we observe that the number of instruments is acceptable across the 12 regressions. The AR (2) statistics indicate that the regressions do not suffer from a correlation problem. Regarding the exogeneity of the instruments, the Hansen test indicates satisfying results in ten regressions. The results for knowledge-intensive services in Table 6 (growth in value added) is close to the critical value, whereas the test indicates that the orthogonality conditions are not fulfilled in Table 6 for less knowledge-intensive services. Our overall conclusion on the test statistics is that model specifications are valid. Comparing the dynamic GMM results with both OLS and random effects regressions, we find that the general pattern of the results is similar. The main difference is the size of the estimates.\textsuperscript{6}

6 Conclusions

This paper has studied the post-entry evolution of 23,000 new entrants in Sweden throughout the critical first 5-year period in the market. Confirming previous empirical studies, our data showed that most of the firms disappeared early and death risk was largest in metro cities. However, applying econometric analysis using both discrete hazard and dynamic GMM models, we also provided support for the Hoover and Vernon (1959) predictions that central locations are advantageous for new businesses. In part, the seemingly contradiction between theories on spatial importance of new ventures and empirical results may be repealed by considering whether the starters are (1) genuinely new entrants (GNE) or ex-employees entrants (spin-offs), (2) knowledge/technology intensive or not and (3) manufacturing firms or services. With this categorization of the entrepreneurial firms, we are able to provide new insights to the literature. Four different types of locations of the new firms are identified: metro cities, metro regions outside the metro cities, urban areas outside metro regions and other places which we labeled as rural areas. The reference group across the regressions is genuinely new entrants located in rural areas.

In a previous study, Renski (2009) found that new knowledge-intensive firms in central cities in the United States have higher failure rates than firms entering the market in other places. In line with Renski, our hazard estimates on GNEs show that metro-city location is associated with higher death risk among knowledge-intensive starters. But we also find high death risk among less knowledge intensive services and less technology intensive manufacturing firms. Adding spinoffs (which account for about 1 out of 10 new firms in Sweden) to the analysis, the results are even more complex compared to prior literature. Indeed, spinoffs in metro cities are somewhat less likely to survive than spinoffs in other areas. But comparing spinoffs with all other new entrants, we show that manufacturing spinoffs in metro cities are as viable as manufacturing GNEs outside metro cites. Moreover, service spinoffs in metro cities actually have lower failure risk than GNEs in services whether they are located outside or inside a metro area.

There are two main messages from the analyses on value added controlling firm size and other firm characteristics among start-ups surviving their first 5 years. First, no favorable locational conditions can be found among GNEs. In contrast, manufacturing spinoffs in metro cities have significantly higher value added than all other corresponding new starters. Second, regarding genuinely new entrants in services, the location is also found to be neutral with respect to value added. But for each of the four geographical locations considered, the average level of value added among spinoffs is substantially higher compared to other entrepreneurial firms. Since valued added controlling for firms size is a productivity measure, our results suggest that manufacturing spinoffs in metro cities are more productive than other new manufacturing firms, while spinoffs in services are more productive than other new services, irrespective of location.

The final analysis concerns variation in growth, with the following main findings. No difference in productivity or employment growth can be found among start-ups in manufacturing regarding the origin of the firms (GNEs of spinoffs) or location within industry sectors. The result is in contrast to several other studies including Acs et al. (2007) which claims that the growth of newborn firms vary with location attributes, and Nicolaou and Birley (2003) and Acs et al. (2009) which suggest that spinoffs are more

\textsuperscript{6} For the robustness check, OLS and random effect models are also estimated. The results are available upon request.
prone to take advantage of agglomerations than other firms. One deviation result in our study should be noted. Spinoffs in medium low and low manufacturing located in metro cities are less successful in employment growth than all other starters within this industry classification.

Regarding growth in services, we find that entrepreneurial firms in metro cities have significantly higher productivity growth than other entrepreneurs. This is true for both GNEs and for spinoffs, as well as for knowledge intensive firms and other new firms. But the benefit of metro cities is largest among knowledge intensive firms and the metro city productivity premium is larger for knowledge intensive spinoffs than for other knowledge intensive services.

Higher employment growth than the reference group could only be found within the group of less knowledge intensive services. Moreover, within this category of new firms the higher employment growth is limited to GNEs and spinoffs in metro cities plus spinoffs in urban areas. This final finding is somewhat surprising and in contrast to, for example, the paper by Renski (2009) reporting that new knowledge-intensive firms in central cities have faster employment growth than corresponding firms in other places in the United States.

What main implications may be driven from the study? Spinoffs, technology, knowledge and agglomerations are often targeted as important areas for policy makers’ ambitions to transform entrepreneurship into productivity, employment and growth. We may conclude that a successful policy needs to account for a more nuanced and broader view on entrepreneurship.

Acknowledgments The authors would like to thank three anonymous referees and the handling editor for helpful comments and suggestions.

References


Inherited Advantage and Spinoff Success *

Pardis Nabavi†

Abstract
This paper focuses on exports, innovation, tenure and management and investigates how the incumbent firm characteristics affect the viability of its spinoff. Using comprehensive Swedish employer-employee panel data sets, three possible outcomes are identified for spinoffs: survival, acquisition and complete exit from the market. While experience from exporting parent has a significant and positive effect on spinoff survival, no spillover effect from an innovative parent can be found. However, taking the managerial experience in the incumbent firm into account, there is some weak evidence of a positive link between the innovative parent and the survival of the spinoff.

Keywords: Entrepreneurship, organizational heritage, spinoff.
JEL-Codes: C25, L26, M13

*I am grateful for the helpful comments I received from Hans Lööf, Karl Wennberg and participants of SEI doctoral consortium, Imperial College London, 2013. The comments substantially improved the paper.
†Department of Industrial Economics and Management, Royal Institute of Technology Stockholm
1 Introduction

Inherited advantage and success of spinoffs have attracted growing attention over the past decades. There is a broad consensus that entrepreneurial ventures founded by ex-employees of incumbent firms play a vital role in the dynamics of the economy. Contributions from several different research disciplines have established some robust stylized facts such as the fact that managers and technical specialists are more likely to found firms, pulled spin-off performance is better than all other types of start-ups, spinoffs that enter the same industry as their parent perform better than other spin-offs, and spin-offs from better-performing firms have better performances. These findings are generally indicating that the incumbent firm is some form of knowledge pool, training camp or integrated network that is beneficial for the start-ups via the knowledge of ex-employees.

Over the past few years, the access to employer-employee micro data set has provided an opportunity to deepen the understanding of the knowledge transfer mechanisms and inherited advantage. For recent examples, see Eriksson and Moritz Kuhn (2006), Elfenbein et al. (2010), Sorensen and Phillips (2011), Andersson et al. (2012), Dick et al. (2013), and Andersson and Klepper (2013). This paper is within this emerging strand of spinoff research.

It would be desirable to further differentiate between various characteristics of the parent firms and more studies need to focus on the performance of the entrepreneurial spawns based on different categories of their parent firms. Therefore, the aim of the present study is to contribute to the literature by examining whether innovative incumbent firms or companies engaged in export spawn more viable entrepreneurial new ventures. The model controls for other firm characteristics, such as productivity, human capital, size, ownership and industry. We are also exploiting the information on the ex-employee’s job-position and tenure in the father firm and, moreover, their overall experience on the labour market. The analysis is based on comprehensive employer-employee data sets on the entire Swedish private sector. The goal of this systematic study, which considers the properties of the different categories of spawning companies and also the background of the start-up entrepreneurs, is to fills a gap in the spinoff literature.

In order to pursue this objective, we identify three possible market outcomes of the new venture. While almost all existing literature only distinguishes between survival and exit, we also consider that the firm can have a successful exit in
terms of being acquired by another firm.

The following main results emerge from this study: (i) spinoffs from exporting firms have a larger market success than other spinoffs, (ii) innovative parents do not produce more viable offspring than other firms, (iii) longer tenure in parent has a significant positive effect on the survival of spinoffs, (iv) accounting for both tenure and managerial experience, the advantage of having an exporting father firm reduces, while the result is the opposite for ex-employees from innovators.

The paper proceeds as follows. Section 2 reviews recent literature on spinoffs. Section 3 presents the data, formulates the methodological approach and specifies the empirical model. Section 4 reports new empirical evidence on the relationship between incumbent firms and their spinoff. Section 5 provides concluding remarks and suggestions for further research.

2 Literature review and research questions

There is an abundance of evidence that spinoffs perform better than other types of start-ups. This section starts with some theoretical underpinnings that can explain why ex-employees are more suitable than other entrepreneurs to start a new venture. Several key elements in evolutionary models on technical change and industry dynamics are of interest, such as cumulativeness, tacitness and the multi-person nature of knowledge and skills. The theoretical background, some main findings that have been made in recent contributions in the spinoff literature, and the research questions are presented.

2.1 Theoretical background

In contrast to the orthodox neoclassical theory, the Schumpeterian and evolutionary models predict an economy with lasting performance heterogeneity across firms. Empirically, the variability between firms is confirmed in both cross-sectional and time-series dimensions. Studying French data, Griliches and Mairesse (1998) find that “something like Mandelbrot’s fractal phenomenon seemed to be at work.” The observed heterogeneity was just as much different within the total manufacturing as between different bakeries. A similar pattern has been documented for other countries. Exploring the role of micro heterogeneity for aggregate productivity growth in the U.S., Hulten et al. (2001) identify substantial variation in performance in the same or a narrowly defined
sector. Moreover, the heterogeneity tends to be persistent over time.
Extensive research demonstrates the difficulty of the individual firm in imitating and adopting the best practices among its competitors. At the same time, a pervasive empirical finding in the recent literature is that spinoffs are able to benefit from father firms. Previous literature has highlighted some key factors that may account for firm and plant level differences in performance. Dosi and Nelson (2010) argue that replication of technological knowledge concerning processes, organizational arrangements, and products is difficult and often quite expensive. Mostly, firms are not aware of the best practice, and even if they were, they would probably not have the capability to develop or use it. Dosi and Nelson (2010) discuss the main reasons why technological knowledge is difficult to transfer between firms: (1) it is partly tacit, (2) it is embodied in complex organizational practices, (3) technological leads and lags can be linked to high initial costs, and (4) indivisibility (“Half of a statement about the property of a technology is not worth half of the full one: most likely it is worth zero”). Dosi and Nelson (2010) moreover, emphasize that lack of convergence towards best techniques has little to do with the legal system for intellectual proprietary rights.

Innovative capabilities appear to be even more difficult to spread and imitate than capabilities associated with production efficiency and organizational arrangements. Additional candidates to those discussed above, for explaining why firm’s innovativeness is particularly difficult to imitate, include the (i) distinction between individual skills and organizational skills and (ii) accumulation of knowledge through persistent engagement in R&D. Starting with the first one, a likely reason why innovation capabilities appear to be highly skewed (with a small proportion of firms in each segment or sector responsible for a large proportions of innovations) is that the necessary pieces of knowledge and skills are distributed across many individuals. Thus, innovation is often characterized by indivisibility, as described above. Often the firm needs to know or have access to the whole concept in order be a successful innovator. Regarding persistency and accumulation, prior experience from related innovation projects can create internal spillovers and tend to reduce the costs of new innovations (Nelson and Winter, 1982).

2.2 Empirical findings in prior studies

Using case-study approaches, important findings on the link between spinoffs
and their background have been reported. Bhide (1994) found that 71 percent of the founders he questioned exploited ideas they had while working for their previous employer.

A number of more recent researchers have used employer-employee data to study the effect of heritage on performance of spinoffs (Eriksson and Moritz Kuhn, 2006; Dahl and Reichstein, 2006, 2007; Sorensen and Phillips, 2011; Andersson et al., 2012; Andersson and Klepper, 2013; Dick et al., 2013). These studies have contributed to a deeper understanding of the mechanisms that distinguish spinoffs from other new firms and the idiosyncratic factors determining why some spinoffs are more successful than others. Andersson and Klepper (2013) summarize some main findings from this literature as follows: (a) high-level workers, including managers and technical specialists, are more likely to found firms, (b) worker tenure reduces the probability of leaving to found a spinoff, (c) pulled spinoffs, are initially larger and perform better than all other types of start-ups, (d) spinoffs that enter the same industry as their parent perform better than other spin-offs, (e) spin-offs from better-performing firms perform better.

A small strand of the entrepreneurship literature studies the presence of spinoffs on international markets. The evidence suggests that new ventures gain additional knowledge as they diversify further into international markets similar to those of the incumbent firms (Oviatt and McDougal, 1994; Barkema and Vermeulen, 1998; Zahra et al., 2000; Westhead et al., 2001). However, we know very little about exporting firms as an incubator for start-ups.

The innovativeness of the incumbents is another background that could influence the performance of new firms. Andersson and Klepper (2013) find that spawn spinoffs of MNEs have higher performance and this can be explained by the amount of their R&D investments. Conflicting evidence is reported by von Rhein (2008). Analyzing 33 German automobile spinoffs, she finds no difference in survival rate between spinoffs from innovative and non-innovative parents.

In order to share common knowledge with the incumbent firm, the new venture needs in-house capacity for absorbing external knowledge. Consistent with seminal papers by Cohen and Levinthal (1990) and Rosenberg (1990), a recent study by Elfenbein et al. (2010) suggests that the firm’s initial supply of knowledge and know-how may increase its capability to adapt to changes and survive. In our study, we assume that this in-house capacity of the spinoff can be measured by the tenure and managerial experience of the ex-employees in the father firm.
Studying all the start-ups in the Danish manufacturing sector, Dahl and Reichstein (2006) show that longer tenure at the incumbent parent firm increases the life chances of spinoffs. They argue that their findings imply that longer tenure achieved at the parents firm results in superior knowledge about the organizational routines and therefore enables them to perform better. But tenure is only one kind of information on experience from the incumbent firm. Lazear (2005) argues that a variety of skills ranging from application knowledge and management skills are required for entrepreneurship. Previous studies have also shown that managerial experience has an important effect on switching to entrepreneurial spinoffs (Phillips, 2002; Dencker et al., 2009). Furthermore, Dahl and Reichstein (2007) findings suggest that the likelihood of survival of spinoffs is determined not just by level of experience but also by the type and source of experience in parents.

Due to data limitation, most existing studies on morality risk for new ventures employ the binary alternative survival versus exit. However, exit through merger and acquisition (M&A) may be an indicator of the success of the entrepreneur or the management team (Headd, 2003; Dahl and Reichstein, 2007; Wennberg et al., 2010; Cefis and Mansili, 2012; Weterings and Marsili, 2015). In this paper, we are able to separate M&A from exit due to failure.

2.3 Research questions

The review of existing studies on spinoffs indicates that the more knowledge available from the prior employer, the greater the exploitation opportunities in the new company. Both theoretical models and empirical studies suggest that the capability to benefit from knowledge within the incumbent firms is linked to the absorptive capacity of the ex-employees.

In this paper, tenure and managerial experience in the parent firm are used as indicators for absorptive capacity. We distinguish between different categories of incumbent firms depending on their exporting and innovation activities. Since exporting firms in general are more productive than other companies, spinoffs from exporters are expected to be more viable than spinoffs from non-exporting firms. In contrast, spin-offs from innovative companies do not have better market opportunities than other ex-employee start-ups. The viability is measured as either survival or experiencing mergers and acquisition during the first five years on the market. Taking tenure and managerial background into account, and combining them with the parents characteristics, they are assumed to have
the greatest importance for transferring knowledge from innovative firms.

3 Data and methodology

3.1 Data and sample

Our data is assembled from several sources. The first is register information on firms and establishments provided by Statistics Sweden and constructed from audited information based on annual reports. The second data source is official information on people employed in the Swedish labour market. The third data source we use is patent applications from the EPO worldwide database PATSTAT. Patents, whether granted or not are assumed to be a proxy for innovation and knowledge-generating activities within the incumbent firm. Moreover, we can match all the firms with trade statistics in order to obtain information on their exporting activities and their new export products. Together with patents, new export products form our proxy for innovativeness.

The original data set includes observations on virtually all private Swedish manufacturing and service firms between 1997 and 2011 and information on all employees in these firms goes back to 1986. From this data we identify new ventures directly tied to other firms through employment migration. Interchangeably, these firms are labelled as entrepreneurial spawns, employee start-ups and spinoffs.

Following Andersson and Klepper (2013) and similar to Eriksson and Moritz Kuhn (2006), and Dahl and Reichstein (2007), the employee start-ups in this study are recognized by observing ex-employees in both the parent company and the new firm. If they were a minority in the parent firm the year before the transition to new firm, but a majority in the new firm the year after the transition, we consider these firms as entrepreneurial spawns or spinoffs. The method starts by identifying whether a majority of employees in a new firm in a particular year were also a majority in another firm the year before. Then the firm which was the employer of the majority of employees last year is called the parent firm and if the new firm is not a result of a merger-process, then the start-up firm is considered as a spinoff.

We have imposed several constraints on the incumbent offspring to be considered as a spinoff. First, the new entrants are restricted to firms with 2-10 employees initially. The upper limit is imposed to separate firm formation due
to outsourcing and M&A from real spinoffs. The lower limit is motivated by a requirement that start-up needs to have at least two employees in order to be defined as an employee start-ups. Second, the new venture must be an independent firm when they enter the market, which implies that no firm owned by a domestic or a foreign group are included in the using data. Third, in order to have sufficient information on both the parent firms and their descendants, we restrict the analysis to seven cohorts to track the incumbents for the last four years before the spawning and the new firms over a five-year period. The first cohort consists of spinoffs in 2001 and the last cohort of spinoffs entered the market in 2007. Furthermore, we exclude spinoffs entering into primary sectors (Agriculture, Fishing and Extraction; NACE 1-14) and the hotel and restaurant sector (NACE 55) as these industries are known to have different regularities and the entrance and survival patterns in these sectors are not similar to the rest of the economy. It should be noted that, in contrast to some prior studies, we do not narrow down the definition of spinoffs to firms that are spawned into the same industry as the father firm. However, in the regression analysis, we exploit information on whether the new firm operates in the same five-digit industry as the parent.

The using data consists of 5,833 unique spinoffs which enter the market during 2001-2007 period and have about 70% survivors after five years, as illustrated in Table 1. The spinoffs are spawned from 5,421 unique parents where 87% of them spawned only one and 8% spawned two spinoffs. It is worthwhile to note that only 2% of the incumbent firms have more than four entrepreneurial spawns during this seven-year period (Table 2).

Table 1: Cohorts of spinoffs between 2001 and 2007, survival and year of observation of spinoffs in the study

<table>
<thead>
<tr>
<th>Year</th>
<th>2001</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
<th>2011</th>
<th>Surv</th>
</tr>
</thead>
<tbody>
<tr>
<td>2001</td>
<td>838</td>
<td>757</td>
<td>681</td>
<td>652</td>
<td>604</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.72</td>
</tr>
<tr>
<td>2002</td>
<td>785</td>
<td>722</td>
<td>652</td>
<td>588</td>
<td>559</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.71</td>
</tr>
<tr>
<td>2003</td>
<td>801</td>
<td>748</td>
<td>671</td>
<td>624</td>
<td>586</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.73</td>
</tr>
<tr>
<td>2004</td>
<td>800</td>
<td>742</td>
<td>684</td>
<td>635</td>
<td>592</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.74</td>
</tr>
<tr>
<td>2005</td>
<td>812</td>
<td>739</td>
<td>672</td>
<td>616</td>
<td>562</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.69</td>
</tr>
<tr>
<td>2006</td>
<td>835</td>
<td>758</td>
<td>699</td>
<td>625</td>
<td>577</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.69</td>
</tr>
<tr>
<td>2007</td>
<td>962</td>
<td>878</td>
<td>805</td>
<td>744</td>
<td>700</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.73</td>
</tr>
</tbody>
</table>
Table 2: Percentage of parents with one or more spawned new ventures

<table>
<thead>
<tr>
<th>Number of spawned ventures</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>86.6</td>
</tr>
<tr>
<td>2</td>
<td>8.3</td>
</tr>
<tr>
<td>3</td>
<td>2.0</td>
</tr>
<tr>
<td>4</td>
<td>1.1</td>
</tr>
<tr>
<td>&gt;4</td>
<td>2.0</td>
</tr>
</tbody>
</table>

3.2 Variables

Since inherited advantage and success of spinoffs have been found to be closely interlinked, prior literature emphasizes the importance of observing a wider range of firm and employee characteristics to understand the genealogical process of spillovers (Sorensen and Phillips, 2011). In our effort to embrace this insight, we consider a broad set of explanatory variables including both the old and the new company and the employees in these companies. The variables are presented and defined in Table A1.

3.2.1 Dependent variable

The dependent variable captures the three possible outcomes of spinoffs on the market during the initial critical five-year period. The possible outcomes are survival as an independent firm, exit through M&A and complete exit from the market. While many existing studies only consider survival as a successful outcome, exiting by M&A is also considered as a market success. M&A in our study includes processes of buying, selling, dividing and combining companies.

3.2.2 Key explanatory variables

The key explanatory variables are exporting, innovation, tenure and managerial experience. The incumbent firm is defined as exporter if it has been present in international markets during at least two of the four years before the spawn. The trade literature has shown that good firms become exporters, and that both growth rates and levels of success measures are higher ex-ante for exporters (Bernard and Jensen, 1999). We assume that the spinoff benefits not only from the organization and knowledge within the exporting parent, but also from access to networks of global customers.

A second potential inherited advantage is conceived by an innovative parent. However, the literature review presented in section 2 suggested that innova-
tiveness tends to be sticky and not easily transferred across firms. We identify innovative parents as firms which had one patent application or more, or which introduced at least one new export product on the market during the four years before spawning. It should be noted that innovative exporters are only considered to be innovative parents to separate these two different effects.

The variable tenure is defined as the average of the tenure in parent firms relative to total experience on the labour market. This measure will help us answer the question “How does the length of job tenure in the parent firm impact the success of spawns?” (Chatterji, 2009). In the empirical analysis, we also control for total experience.

The final key explanatory variable is managerial position in the incumbent parents. Lazear (2005) argues that variety of skills is important for entrepreneurship. While Management skills have been found to increase the likelihood of spawning (Andersson and Klepper, 2013), it can also be assumed that managers have greater access than other ex-employees to knowledge about the organization and routines in the parent firm. Therefore, a positive relation is expected between this variable and likelihood of success.

Interacting export and innovation respectively with tenure and managerial experience enables us to deepen the examination of the inherited advantage of the incumbent firm. Based on the literature discussed in Section 2, it can be assumed that tenure and managerial experience is more important if the incumbent firm is an innovator rather than an exporter.

3.2.3 Control variables

The control variables are related to the characteristics of both the incumbent firms and their spinoffs. Prior literature has shown that spinoffs entering the same industry as their parent perform better than other spinoffs. To account for this effect, we include a dummy if both firms operate in the same five-digit industry. There is a broad agreement in the literature that human capital is a key asset of the firm. We measure human capital as fraction of employees with at least three years of university education, and this variable is observed for both the incumbent and the new venture. Since both inherited advantage and spinoff success are closely associated with productivity, we use this control in both categories of firm (labour productivity in the incumbent firm and value added in the new venture). We also control for size of the parent firm which is total number of employees prior to spawning and initial number of employees.
in the new entrant.

The relationship between parent firm and the spawn firms may differ conditional on whether there was a strong push effect for starting a spinoff. Therefore, three distinctions have been made based on the activity of the parent firms: first, incumbents which continue being active in the labour market, *Parent Active*; second, incumbents which exited the same year or within a one-year period of spawning, *Parent Failure*. Finally, those incumbents which experienced a merger or acquisition process at the same time as launch of spinoff are categorized as *Parents M&A*. Eriksson and Moritz Kuhn (2006), Dahl and Reichstein (2007), and Andersson and Klepper (2013) have shown that spinoffs can have different characteristics based on the status of their parents (So called pushed and pulled spinoffs).

As discussed above, we control for average level of ex-employees’ *experience* before spawning. This variable is supposed to pick up the effect of the general experience, while the tenure in parent only reflects the relative knowledge specific to the parent. Other controls include ownership structure of both spinoffs and their parents, sector dummies and time effect (year dummies).

### 3.3 Summary statistics

Table 3 presents descriptive statistics. The upper part of the table reports statistics for the 5,421 parent firms, the middle for the founders of the new firms, and the bottom section reports summary statistics for 1,363 unique spinoffs that exited the market within the first five years (23%), 285 spinoffs that experienced merger and acquisition process (5%) and the 4,185 remaining spinoffs that continued working after the first five critical years (72%).

One of 20 spinoffs has innovative parents in all groups, while a quarter of the offspring have exporting parents. Consistent with findings from other countries, a substantial fraction of the new firms enter the same market as their parents. It is notable that new entrants that are exiting through the M&A process are typically spawned by larger firms than other new entrants. Less than 20% of the ex-employee start-ups can be considered as push-driven, since the incumbent firm disappeared from the market after the spawning. Not surprisingly, this figure is largest for exited spinoffs (column 3).

Table 3 shows that the founders of survived spinoffs have slightly more labour market experience, while tenure and managerial experience are about the same
### Table 3: Summary statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) Survived Spinoffs</th>
<th>(2) M&amp;A Spinoffs</th>
<th>(3) Exited Spinoffs</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Parent characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Innovative</td>
<td>0.06</td>
<td>0.23</td>
<td>0.05</td>
</tr>
<tr>
<td>Exporter</td>
<td>0.26</td>
<td>0.44</td>
<td>0.28</td>
</tr>
<tr>
<td>Same Industry</td>
<td>0.44</td>
<td>0.50</td>
<td>0.37</td>
</tr>
<tr>
<td>Human Capital</td>
<td>0.13</td>
<td>0.20</td>
<td>0.12</td>
</tr>
<tr>
<td>Emp</td>
<td>362</td>
<td>1563</td>
<td>662</td>
</tr>
<tr>
<td>LP</td>
<td>12.53</td>
<td>2.51</td>
<td>12.64</td>
</tr>
<tr>
<td>Exit</td>
<td>0.17</td>
<td>0.38</td>
<td>0.12</td>
</tr>
<tr>
<td>M&amp;A</td>
<td>0.11</td>
<td>0.31</td>
<td>0.16</td>
</tr>
<tr>
<td>Active</td>
<td>0.72</td>
<td>0.45</td>
<td>0.72</td>
</tr>
<tr>
<td>Uni-National</td>
<td>0.22</td>
<td>0.41</td>
<td>0.16</td>
</tr>
<tr>
<td>Domestic MNE</td>
<td>0.14</td>
<td>0.34</td>
<td>0.20</td>
</tr>
<tr>
<td>Foreign MNE</td>
<td>0.13</td>
<td>0.34</td>
<td>0.14</td>
</tr>
<tr>
<td>Independent</td>
<td>0.51</td>
<td>0.50</td>
<td>0.50</td>
</tr>
<tr>
<td><strong>Characteristics of ex-employees in spinoff transition</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tenure</td>
<td>0.33</td>
<td>0.21</td>
<td>0.30</td>
</tr>
<tr>
<td>Managerial</td>
<td>0.06</td>
<td>0.15</td>
<td>0.06</td>
</tr>
<tr>
<td>Experience</td>
<td>15.41</td>
<td>4.18</td>
<td>14.23</td>
</tr>
<tr>
<td><strong>Spinoff characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Initial Emp</td>
<td>3.47</td>
<td>1.87</td>
<td>4.13</td>
</tr>
<tr>
<td>Emp</td>
<td>4.45</td>
<td>5.46</td>
<td>4.63</td>
</tr>
<tr>
<td>Human Capital</td>
<td>0.14</td>
<td>0.26</td>
<td>0.10</td>
</tr>
<tr>
<td>Valued Added</td>
<td>13.90</td>
<td>2.03</td>
<td>13.26</td>
</tr>
<tr>
<td>Uni-National</td>
<td>0.06</td>
<td>0.24</td>
<td>0.07</td>
</tr>
<tr>
<td>Domestic MNE</td>
<td>0.01</td>
<td>0.09</td>
<td>0.01</td>
</tr>
<tr>
<td>Foreign MNE</td>
<td>0.02</td>
<td>0.13</td>
<td>0.02</td>
</tr>
<tr>
<td>Independent</td>
<td>0.91</td>
<td>0.28</td>
<td>0.91</td>
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<tr>
<td>Manufact HighMedium tech</td>
<td>0.07</td>
<td>0.25</td>
<td>0.06</td>
</tr>
<tr>
<td>Low Tech Manufact &amp; Constr</td>
<td>0.22</td>
<td>0.42</td>
<td>0.19</td>
</tr>
<tr>
<td>Knowledge Intensive Services</td>
<td>0.35</td>
<td>0.48</td>
<td>0.39</td>
</tr>
<tr>
<td>Other Services</td>
<td>0.36</td>
<td>0.48</td>
<td>0.36</td>
</tr>
<tr>
<td>Observations(Unique)</td>
<td>20,925</td>
<td>(4,185)</td>
<td>689</td>
</tr>
</tbody>
</table>

Observations(Unique) = 20,925 (4,185) 689 (285) 3,331 (1,363)
for the three groups of spinoffs. Concerning the new ventures, all are independent initially by definition and more than 90% remains independent. The table reports that 7 out of 10 spinoffs entered knowledge-intensive business services or other services.

3.4 Empirical strategy

The objective of the study is to analyze how innovation and export activities of parent firms influence the performance their spinoffs. In the empirical analysis, we use a competing risk model for time-to-event data. Three outcome events are possible: failure, exit by M&A, or survival. The outcomes are observed at the end of each year. We apply a log-likelihood function of the competing risks. The preferred model is a complementary log-log approach. We also report regression results from a multinomial logit model. A basic assumption in both models is that the hazard rate distribution follows a generalized form of the logistic function. This assumption is common for non-proportional hazard models and when the data set includes firm-year observations (Allison, 1982; Jenkins, 1995, 2005). The hazard rate for firm $i$ with $j$ exit mode is defined as:

$$
\lambda_{ji}(t) = \frac{\exp(\beta_j X_{it})}{1 + \sum_{j'=1}^{J} \exp(\beta_{j'} X_{it})}
$$

(1)

where $X_{it}$ is a vector of explanatory variables. The model is well suited to the analysis of longitudinal data sets because it can accommodate both time-constant and time-varying independent variables (Jenkins, 2005) and has been applied by Weterings and Marsili (2015), Cefis and Marsili (2012) and Fontana and Nesta (2009) to study firm exit modes.

Moreover, in order to take into account possible unobserved heterogeneity (or frailty), we also use complementary Log-Log model with the following hazard function:

$$
\lambda_{ji}(t) = 1 - \exp\{-\exp[\beta_j X_{it} + \theta_i]\}
$$

(2)

where $\theta_i$ is the baseline hazard function.

4 Results

Table 4 reports the results of the complementary log-log estimation method.
This is our preferred model since it accommodates unobserved firm heterogeneity. The dependent variable indicates whether the market introduction of the new venture is a success in terms of survival or M&A, or whether it is a failure that results in the exit. The outcome variable is observed over the first five critical years on the market. The estimated coefficients are reported in exponential form, and the base outcome is failure of the spinoff. Reading the tables, it should be noted that estimates of odd ratios below 1 indicate increased likelihood to exit, while an estimate above 1 indicates increased chances of success. Results from two alternative models are presented. While the variables of interest are included in both models, model I only accounts for characteristics related to the incumbent firm. Model II also controls for the spinoff characteristics and this is the preferred specification. With reference to the base alternative exit, the upper part of Table 4 shows the relative chance of survival, and the lower part refers to odds of M&A.

4.1 Survival

Starting with survival outcome, the focus is on inherited advantage from the parent company. The first row shows that the odd ratios for innovative parent are just above unity in both model I (1.117) and model II (1.034). Neither of the estimates is significantly different from the base alternative exit. The results show that innovativeness of the parent has no impact on the survival chances of the spinoffs.

Looking then at the impact from an exporting parent, the estimates are positive (1.293 and 1.240) and highly significant. Irrespective of whether this reflects inherited knowledge about processes, routines and other internal activities in the parent firm (Helfat and Lieberman, 2002), or access to similar international networks and market alternatives as the incumbent firm, the new venture benefits from exporting experience.

Next, we consider importance of tenure and managerial experience. While the estimates for tenure are large in size (2.080 and 1.851) and highly significant, no effect of managerial experience can be found. Managerial experience is measured as share of employees in the new firm that held a managerial position in the parent firm in the year before spawning. The results for tenure are consistent with Agarwal et al. (2004) and Klepper and Sleeper (2005), and can be interpreted as indicating that the ability of the entrepreneurial spawns was most
Table 4: Complementary Log-Log analysis
Characteristics of parent firms and ex-employees in transition to the new firm

<table>
<thead>
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<th></th>
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<th></th>
<th></th>
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<tbody>
<tr>
<td><strong>Survival</strong>&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
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<tr>
<td>Innovative</td>
<td>1.117</td>
<td>(0.19)</td>
<td>1.034</td>
<td>(0.14)</td>
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<tr>
<td>Exporter</td>
<td>1.293***</td>
<td>(0.13)</td>
<td>1.240***</td>
<td>(0.10)</td>
</tr>
<tr>
<td>Tenure&lt;sup&gt;b&lt;/sup&gt;</td>
<td>2.080***</td>
<td>(0.27)</td>
<td>1.851***</td>
<td>(0.21)</td>
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<tr>
<td>Managerial&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.797</td>
<td>(0.14)</td>
<td>0.867</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Innovative×Tenure</td>
<td>0.918</td>
<td>(0.38)</td>
<td>1.005</td>
<td>(0.33)</td>
</tr>
<tr>
<td>Innovative×Managerial</td>
<td>1.485</td>
<td>(1.03)</td>
<td>1.188</td>
<td>(0.63)</td>
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<tr>
<td>Exporter×Tenure</td>
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<td>(0.14)</td>
<td>0.588***</td>
<td>(0.12)</td>
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<td>Exporter×Managerial</td>
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<td>0.974</td>
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<td>(0.05)</td>
<td>1.155***</td>
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<tr>
<td>HC</td>
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<td>(0.11)</td>
<td>1.079</td>
<td>(0.14)</td>
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<tr>
<td>Emp</td>
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<td>(0.00)</td>
<td>1.000</td>
<td>(0.00)</td>
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<td>(0.01)</td>
<td>1.004</td>
<td>(0.01)</td>
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<td>M&amp;A&lt;sup&gt;c&lt;/sup&gt;</td>
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<td>(0.07)</td>
<td>0.906</td>
<td>(0.05)</td>
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<td>Active&lt;sup&gt;c&lt;/sup&gt;</td>
<td>1.165***</td>
<td>(0.06)</td>
<td>1.146***</td>
<td>(0.05)</td>
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<tr>
<td>Uni-National&lt;sup&gt;d&lt;/sup&gt;</td>
<td>1.008</td>
<td>(0.05)</td>
<td>0.984</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Domestic MNE&lt;sup&gt;d&lt;/sup&gt;</td>
<td>1.116</td>
<td>(0.08)</td>
<td>1.050</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Foreign MNE&lt;sup&gt;d&lt;/sup&gt;</td>
<td>1.077</td>
<td>(0.08)</td>
<td>1.044</td>
<td>(0.06)</td>
</tr>
<tr>
<td><strong>M&amp;A</strong>&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Innovative</td>
<td>0.963</td>
<td>(0.45)</td>
<td>1.085</td>
<td>(0.53)</td>
</tr>
<tr>
<td>Exporter</td>
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<td>0.793</td>
<td>(0.22)</td>
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<td>Tenure&lt;sup&gt;b&lt;/sup&gt;</td>
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<td>(0.40)</td>
<td>1.461</td>
<td>(0.54)</td>
</tr>
<tr>
<td>Managerial&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.969</td>
<td>(0.51)</td>
<td>0.909</td>
<td>(0.32)</td>
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<tr>
<td>Innovative×Tenure</td>
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<td>(0.29)</td>
<td>0.130</td>
<td>(0.17)</td>
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<td>Innovative×Managerial</td>
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<td>(10.69)</td>
<td>5.603</td>
<td>(12.34)</td>
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<td>Exporter×Tenure</td>
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<td>(0.73)</td>
<td>0.954</td>
<td>(0.67)</td>
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<tr>
<td>Exporter×Managerial</td>
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<td>(2.24)</td>
<td>4.698*</td>
<td>(4.01)</td>
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<td>(0.12)</td>
<td>0.938</td>
<td>(0.13)</td>
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<tr>
<td>HC</td>
<td>0.820</td>
<td>(0.27)</td>
<td>0.867</td>
<td>(0.42)</td>
</tr>
<tr>
<td>Emp</td>
<td>1.000*</td>
<td>(0.00)</td>
<td>1.000</td>
<td>(0.00)</td>
</tr>
<tr>
<td>LP</td>
<td>1.043</td>
<td>(0.03)</td>
<td>1.042</td>
<td>(0.03)</td>
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<td>M&amp;A&lt;sup&gt;c&lt;/sup&gt;</td>
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<td>(0.46)</td>
<td>1.737**</td>
<td>(0.39)</td>
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<tr>
<td>Active&lt;sup&gt;c&lt;/sup&gt;</td>
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<td>(0.29)</td>
<td>1.532**</td>
<td>(0.29)</td>
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<td>Uni-National&lt;sup&gt;d&lt;/sup&gt;</td>
<td>1.028</td>
<td>(0.18)</td>
<td>0.989</td>
<td>(0.17)</td>
</tr>
<tr>
<td>Domestic MNE&lt;sup&gt;d&lt;/sup&gt;</td>
<td>2.027***</td>
<td>(0.38)</td>
<td>1.757***</td>
<td>(0.37)</td>
</tr>
<tr>
<td>Foreign MNE&lt;sup&gt;d&lt;/sup&gt;</td>
<td>1.279</td>
<td>(0.26)</td>
<td>0.984</td>
<td>(0.22)</td>
</tr>
<tr>
<td><strong>Spinooffs Characteristics</strong></td>
<td>No</td>
<td>Yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Year Dummies</strong></td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>24,945</td>
<td>24,945</td>
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</tr>
</tbody>
</table>

Note: Robust standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01
<sup>a</sup> Coefficients are reported in exponential form, the base outcome is failure
<sup>b</sup> Characteristics of Founders in Spinoff Transition, <sup>c</sup> Reference is Parents Exited
<sup>d</sup> Reference is Parents Independent
probably shaped while they were working for the incumbent firms. This ability is not linked to the organizational position of the ex-employee.

The final key variables are the interaction between firm characteristics and ex-employee experience from the parent firm. First, we see that tenure in the innovative firm has no impact on the survival of the spinoff. This supports the previous discussions on tacitness, indivisibility and high upfront cost of innovation. Interestingly, the estimated effect of the interaction between innovation and managerial experience is positive. The size of the estimate is 1.485 in model I and 1.188 in model II. Although neither estimate is significantly different from the reference category, they provide some weak evidence for the assumption that absorptive capacity or particular skills are essential in order to benefit from knowledge associated with innovation activities. Managerial experience might foster such skill.

The interaction variable between exporting and management is close to unity and not significant. However, the estimated coefficient for tenure and export is negative (below unity) and significant. This means that the positive correlation between exporting parent and survival and between tenure and survival becomes weaker if we consider tenure in the exporting incumbent.

Estimated coefficients for control variables show results consistent with the prior literature (see for example Andersson and Klepper, 2013). Employee startups in the same five-digit industry as the incumbent have almost 15% higher probability to survive than firms outside the industry. Being spawned from an active parent (or pulled spinoffs) increases the propensity of spinoff survival. Similar results are reported by Eriksson and Moritz Kuhn (2006), Dahl and Reichstein (2007) and Andersson and Klepper (2013).

Controlling for observed heterogeneity among both incumbent firms and their spawned firms and unobserved heterogeneity as well, Table 4 also reports results that are in conflict with the existing literature. While previous studies suggest that the performance of the parent predicts the performance of the descendants, Table 4 reports that the effect of parent’s size, human capital and labour productivity is negligible. Thus, our results question one of the stylized facts in the existing spinoff literature. This finding deserves further research.

The estimated results on the spinoff covariates are presented in Table A.4 in the Appendix. The odd ratios show that spinoff survival chances increase with the value added, the size and experience of the new firm. The estimates for initial size, human capital and physical capital are not significant when we control
for frailty. The ownership variables show a negative link between survival and multinational firms when independent firms are the reference group.

4.2 M&A

The lower part of Table 4 refers to odds of exiting by M&A as compared to failure. Similar to the results for the survival outcome, no significant effect can be found related to prior innovative experience from the parents. The result shows that the estimates for innovative parent are below 1 in model I and above 1 when we control for spinoff characteristics in model II.

The estimated coefficients for the export variable are below unity but non-significant. The tenure variable is positive (above unity) and sizable in Model II (1.461) but not significant. Consistent with the survival estimates presented above, the results indicate a positive correlation between managerial experience and market success measured as M&A. However, the results are outside any acceptable level of significance. The only significant estimated key variable with respect to M&A is the interaction between the managerial position and exporter. The estimate is positive and significant at the 10 percent level.

An interesting result reported in the table is the positive association between a parent with an M&A background and the likelihood of M&A by the spawned firm. This finding is in line with the organizational heritage theory. Moreover, entrepreneurial spawn from Swedish multinational firms has larger likelihood of being acquired. No similar finding can be found for descendants of foreign MNEs. The results show that spinoffs from active parents have a greater chance of being acquired. This is similar to Dahl and Reichstein (2007) findings.

Table A.4 reports the estimates for the spinoff characteristics. The results reveal that the chance of being acquired increases with the employment size of the new venture. Concerning sector classification, Table A.4 shows that knowledge-intensive services are more likely to be acquired than firms in other sectors.

Table A.3 in the Appendix reports the results of the multinomial logit model as a robustness check. The estimated effect is almost the same as the results on survival and M&A presented above.

5 Conclusions

Inherited advantage and success of spinoffs have attracted growing attention over the past decades. Recently, availability of employer-employee data has
provided an opportunity to deepen the understanding of the knowledge transfer mechanisms and inherited knowledge since information from both the new and the old firm can be exploited. Our paper is within this emerging strand of the spinoff research. We apply a panel data approach on a data set which covers the entire Swedish private sector. The paper examines inherited advantages from innovative and exporting companies, while controlling for other firm characteristics, such as productivity, human capital, size, ownership and industry. The information on the ex-employees job position and tenure in the father firm and their overall experience on the labour market is also exploited. The incumbent firms are separated into three groups: (i) non-innovating and non-exporting, (ii) non-innovating and exporting, and (iii) innovating. Distinguishing between failure and exit through M&A, we aim to provide systematic evidence for the relationship between the characteristics of parent firms and the performance of ex-employee start-ups performance. Both survival and merger and acquisition are considered as market success. Consistent with theoretical predictions, the regression results suggest that knowledge inside innovative firms tends to be sticky and not easily transferred to the new venture by the ex-employees. This is reflected in the estimated survival rate. There is no significant difference between the survival rate of the spinoffs from innovative parents and those spinoffs with neither innovation nor exporter parents. However, taking managerial experience in the incumbent firm into account, we find some weak evidence of positive spillover from the innovative parent. In contrast to the brittle link between innovators and their heirs, spinoffs from exporting firms are found to have a larger market success than other spinoffs. The result for exporters is not affected by tenure or managerial experience. A tentative conclusion is that knowledge about processes, routines, markets, other internal activities, and international network are probably less complicated to learn and exploit than knowledge about innovative activities. While the study provide new insights into how entrepreneurial ventures founded by ex-employees of incumbent firms vitalize the dynamics of the economy, the results also confirm many previous findings and question some results in existing studies. Moreover, there are several unanswered questions in this study. One possibility for future research is to focus on spinoffs involved in M&A processes and identify whether they are performing differently in ex-employee new ventures. Other indicators of performance of the spinoff can be considered. Moreover, another important area for further research is to include CEO and boards of directors in the analysis on the links between incumbent firms and spinoffs.
References


6 Appendix
<table>
<thead>
<tr>
<th>Variables Name</th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td><strong>Parent characteristics</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Innovative</strong></td>
<td>Parents with patent or new export product the last four year before spawning</td>
</tr>
<tr>
<td><strong>Exporter</strong></td>
<td>Parents present in international market during at least two of the four years before the spawn</td>
</tr>
<tr>
<td><strong>Same Industry</strong></td>
<td>Spinoff working in the same five-digit industry as parents</td>
</tr>
<tr>
<td><strong>Emp</strong></td>
<td>Parents Number of Employees before spawning</td>
</tr>
<tr>
<td><strong>LP</strong></td>
<td>Logarithm of value added per employee of parent the year before spawning</td>
</tr>
<tr>
<td><strong>Human Capital</strong></td>
<td>Share of employees with at least three years of university education before the spawn</td>
</tr>
<tr>
<td><strong>Failure</strong></td>
<td>Exited the same year or within a one year period of spawning</td>
</tr>
<tr>
<td><strong>M&amp;A</strong></td>
<td>Gone through merger and acquisition process the same time as they spawned</td>
</tr>
<tr>
<td><strong>Active</strong></td>
<td>Spinoff with active parents</td>
</tr>
<tr>
<td><strong>Uni-National</strong></td>
<td>Parent members of a domestic group</td>
</tr>
<tr>
<td><strong>Domestic MNE</strong></td>
<td>Parent members of a domestic multinational group</td>
</tr>
<tr>
<td><strong>Foreign MNE</strong></td>
<td>Parent members of a foreign multinational group</td>
</tr>
<tr>
<td><strong>Independent</strong></td>
<td>Non-affiliated parent</td>
</tr>
<tr>
<td><strong>Characteristics of ex-employees in spinoff transition</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Experience</strong></td>
<td>Average years of work experience of the employees gain before spawning</td>
</tr>
<tr>
<td><strong>Tenure</strong></td>
<td>Average of the tenure in parent firms relative to total experience on the labour market</td>
</tr>
<tr>
<td><strong>Managerial</strong></td>
<td>Share of employees of the spinoff who hold a managerial position in the incumbent parent</td>
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<td><strong>Spinoff characteristics</strong></td>
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<td><strong>Initial Emp</strong></td>
<td>Initial number of employees of the spinoff</td>
</tr>
<tr>
<td><strong>Emp</strong></td>
<td>Number of employees of the spinoff</td>
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<tr>
<td><strong>Human Capital</strong></td>
<td>Share of employees with at least three years of university education</td>
</tr>
<tr>
<td><strong>Value Added</strong></td>
<td>Logarithm of value added</td>
</tr>
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<td><strong>Domestic MNE</strong></td>
<td>Members of a domestic multinational group</td>
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<td><strong>Independent</strong></td>
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Table A.2: Cross-correlation table between spinoff outcome and parents

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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<td>(3) M&amp;A</td>
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<td>1.000</td>
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<td>(6) Same Industry</td>
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<td>(7) Parent M&amp;A</td>
<td>0.027</td>
<td>-0.034</td>
<td>0.022</td>
<td>-0.052</td>
<td>-0.066</td>
<td>-0.018</td>
<td>1.000</td>
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<tr>
<td>(8) Parent Active</td>
<td>-0.040</td>
<td>0.039</td>
<td>-0.005</td>
<td>0.093</td>
<td>0.147</td>
<td>-0.004</td>
<td>-0.571</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>(9) Emp</td>
<td>-0.015</td>
<td>0.007</td>
<td>0.015</td>
<td>0.338</td>
<td>0.122</td>
<td>0.004</td>
<td>-0.065</td>
<td>0.129</td>
<td>1.000</td>
<td></td>
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<tr>
<td>(10) LP</td>
<td>0.008</td>
<td>-0.007</td>
<td>0.000</td>
<td>-0.070</td>
<td>-0.048</td>
<td>0.185</td>
<td>0.019</td>
<td>-0.050</td>
<td>0.037</td>
<td>1.000</td>
<td></td>
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</tr>
<tr>
<td>(11) HC</td>
<td>-0.003</td>
<td>0.004</td>
<td>-0.003</td>
<td>0.090</td>
<td>0.010</td>
<td>0.079</td>
<td>-0.024</td>
<td>0.045</td>
<td>0.048</td>
<td>0.126</td>
<td>1.000</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>(12) Experience</td>
<td>-0.075</td>
<td>0.080</td>
<td>-0.026</td>
<td>0.086</td>
<td>0.107</td>
<td>-0.025</td>
<td>-0.050</td>
<td>0.061</td>
<td>0.059</td>
<td>-0.023</td>
<td>0.013</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(13) Tenure</td>
<td>-0.039</td>
<td>0.040</td>
<td>-0.011</td>
<td>0.021</td>
<td>0.068</td>
<td>0.058</td>
<td>-0.036</td>
<td>0.028</td>
<td>0.028</td>
<td>0.074</td>
<td>-0.076</td>
<td>0.005</td>
<td>1.000</td>
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</tr>
<tr>
<td>(14) Managerial</td>
<td>0.002</td>
<td>-0.004</td>
<td>0.005</td>
<td>-0.023</td>
<td>0.092</td>
<td>-0.083</td>
<td>0.013</td>
<td>-0.022</td>
<td>-0.001</td>
<td>0.055</td>
<td>0.043</td>
<td>0.112</td>
<td>0.034</td>
<td>1.000</td>
</tr>
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Note: Bold values are significant at 95% level
Table A.3: Multinomial Logit analysis
Characteristics of parent firms and ex-employees in transition to the new firm

<table>
<thead>
<tr>
<th>Outcome Variables</th>
<th>(I)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Survival**</td>
<td>1.170 (0.30)</td>
<td>1.070 (0.27)</td>
<td>1.410** (0.21)</td>
</tr>
<tr>
<td>Innovative</td>
<td>3.001*** (0.57)</td>
<td>3.058*** (0.57)</td>
<td>0.716 (0.18)</td>
</tr>
<tr>
<td>Exporter</td>
<td>1.410** (0.21)</td>
<td>1.416** (0.21)</td>
<td>0.811 (0.55)</td>
</tr>
<tr>
<td>Tenure**</td>
<td>1.680 (1.85)</td>
<td>1.180 (1.21)</td>
<td>0.466** (0.17)</td>
</tr>
<tr>
<td>Managerialb</td>
<td>0.913 (0.39)</td>
<td>0.963 (0.39)</td>
<td>0.913 (0.39)</td>
</tr>
<tr>
<td>Innovative × Tenure</td>
<td>1.259** (0.09)</td>
<td>1.259** (0.09)</td>
<td>1.680 (1.85)</td>
</tr>
<tr>
<td>Exporter × Tenure</td>
<td>0.466 (0.17)</td>
<td>0.435 (0.16)</td>
<td>0.466 (0.17)</td>
</tr>
<tr>
<td>Exporter × Managerial</td>
<td>1.017 (0.08)</td>
<td>0.950 (0.07)</td>
<td>1.017 (0.08)</td>
</tr>
<tr>
<td>Same Industry</td>
<td>1.336*** (0.08)</td>
<td>1.280*** (0.08)</td>
<td>1.336*** (0.08)</td>
</tr>
<tr>
<td>HC</td>
<td>1.083 (0.16)</td>
<td>1.001 (0.24)</td>
<td>1.083 (0.16)</td>
</tr>
<tr>
<td>Emp</td>
<td>1.000 (0.00)</td>
<td>1.000 (0.00)</td>
<td>1.000 (0.00)</td>
</tr>
<tr>
<td>LP</td>
<td>1.015 (0.01)</td>
<td>1.006 (0.01)</td>
<td>1.015 (0.01)</td>
</tr>
<tr>
<td>M&amp;Ac</td>
<td>0.961 (0.09)</td>
<td>0.845 (0.09)</td>
<td>0.961 (0.09)</td>
</tr>
<tr>
<td>Activec</td>
<td>1.259*** (0.09)</td>
<td>1.259*** (0.09)</td>
<td>1.259*** (0.09)</td>
</tr>
<tr>
<td>Uni-Nationald</td>
<td>1.194 (0.13)</td>
<td>1.109 (0.12)</td>
<td>1.194 (0.13)</td>
</tr>
<tr>
<td>Domestic MNEd</td>
<td>1.083 (0.11)</td>
<td>1.033 (0.11)</td>
<td>1.083 (0.11)</td>
</tr>
<tr>
<td>Foreign MNEd</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M&amp;A**</td>
<td>0.746 (0.38)</td>
<td>0.759 (0.39)</td>
<td>0.746 (0.38)</td>
</tr>
<tr>
<td>Innovative</td>
<td>0.894 (0.27)</td>
<td>0.931 (0.29)</td>
<td>0.894 (0.27)</td>
</tr>
<tr>
<td>Exporter</td>
<td>1.421 (0.59)</td>
<td>1.757 (0.74)</td>
<td>1.421 (0.59)</td>
</tr>
<tr>
<td>Tenure**</td>
<td>0.788 (0.43)</td>
<td>0.735 (0.43)</td>
<td>0.788 (0.43)</td>
</tr>
<tr>
<td>Managerialb</td>
<td>0.661 (0.84)</td>
<td>0.416 (0.56)</td>
<td>0.661 (0.84)</td>
</tr>
<tr>
<td>Innovative × Tenure</td>
<td>0.980 (2.04)</td>
<td>0.528 (1.22)</td>
<td>0.980 (2.04)</td>
</tr>
<tr>
<td>Exporter × Tenure</td>
<td>0.682 (0.51)</td>
<td>0.526 (0.40)</td>
<td>0.682 (0.51)</td>
</tr>
<tr>
<td>Exporter × Managerial</td>
<td>3.258 (2.59)</td>
<td>4.533 (3.80)</td>
<td>3.258 (2.59)</td>
</tr>
<tr>
<td>Same Industry</td>
<td>0.955 (0.13)</td>
<td>0.910 (0.13)</td>
<td>0.955 (0.13)</td>
</tr>
<tr>
<td>HC</td>
<td>0.820 (0.30)</td>
<td>0.993 (0.55)</td>
<td>0.820 (0.30)</td>
</tr>
<tr>
<td>Emp</td>
<td>1.000* (0.00)</td>
<td>1.000 (0.00)</td>
<td>1.000* (0.00)</td>
</tr>
<tr>
<td>LP</td>
<td>1.046 (0.03)</td>
<td>1.039 (0.03)</td>
<td>1.046 (0.03)</td>
</tr>
<tr>
<td>M&amp;Ac</td>
<td>2.037*** (0.49)</td>
<td>1.561* (0.38)</td>
<td>2.037*** (0.49)</td>
</tr>
<tr>
<td>Activec</td>
<td>1.669*** (0.33)</td>
<td>1.572** (0.31)</td>
<td>1.669*** (0.33)</td>
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<tr>
<td>Uni-Nationald</td>
<td>0.989 (0.18)</td>
<td>0.828 (0.15)</td>
<td>0.989 (0.18)</td>
</tr>
<tr>
<td>Domestic MNEd</td>
<td>2.209*** (0.45)</td>
<td>1.747*** (0.37)</td>
<td>2.209*** (0.45)</td>
</tr>
<tr>
<td>Foreign MNEd</td>
<td>1.381 (0.32)</td>
<td>1.102 (0.26)</td>
<td>1.381 (0.32)</td>
</tr>
<tr>
<td>Spinoffs Characteristics</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
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<td>24,945</td>
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</table>

Note: Robust standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01

*a Coefficients in the Relative Risk Ratios are reported, the base outcome is failure
b Characteristics of Founders in Spinoff Transition, c Reference is Parents Exited
d Reference is Parents Independent
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<th></th>
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<tbody>
<tr>
<td><strong>Survival</strong></td>
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<td></td>
<td></td>
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</tr>
<tr>
<td>Initial Emp</td>
<td>0.961*</td>
<td>0.02</td>
<td>0.989 (0.01)</td>
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<tr>
<td>Emp</td>
<td>1.179***</td>
<td>0.03</td>
<td>1.060*** (0.01)</td>
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<td>HC</td>
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<td>0.19</td>
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<td>Physical Capital</td>
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<td>Valued Added</td>
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<td>1.039*** (0.01)</td>
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<tr>
<td>Experience</td>
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<td>0.01</td>
<td>1.042*** (0.01)</td>
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<tr>
<td>Uni-National^c</td>
<td>1.090</td>
<td>0.16</td>
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<tr>
<td>Domestic MNE^c</td>
<td>0.453***</td>
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<td>0.674** (0.11)</td>
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<td>0.512***</td>
<td>0.11</td>
<td>0.737** (0.09)</td>
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<tr>
<td>Manufacture High-Med</td>
<td>0.876</td>
<td>0.11</td>
<td>0.947 (0.07)</td>
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<tr>
<td>Low Tech Manufact &amp; Constr^d</td>
<td>0.993</td>
<td>0.08</td>
<td>0.993 (0.04)</td>
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<tr>
<td>Knowledge Intensive Services^d</td>
<td>1.017</td>
<td>0.08</td>
<td>0.999 (0.04)</td>
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<tr>
<td><strong>M&amp;A</strong></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Initial Emp</td>
<td>1.105***</td>
<td>0.04</td>
<td>1.135*** (0.04)</td>
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<tr>
<td>Emp</td>
<td>1.194***</td>
<td>0.03</td>
<td>1.079*** (0.02)</td>
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<tr>
<td>HC</td>
<td>0.529*</td>
<td>0.20</td>
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<tr>
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<td>Uni-National^c</td>
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<tr>
<td>Domestic MNE^c</td>
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<td>Foreign MNE^c</td>
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<td>0.39</td>
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<td>Low Tech Manufact &amp; Constr^d</td>
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<td><strong>Year Dummies</strong></td>
<td>Yes</td>
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<td>Yes</td>
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<tr>
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<td>24,945</td>
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</table>

Note: Robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

*a Coefficients in the Relative Risk Ratios are reported, the base outcome is failure

*b Coefficients are reported in exponential form

*c Reference is Independent Firms

*d Reference is Other Services