The Role of Location on Complexity of Firms' Innovation Outcome

Sam Tavassoli

sam.tavassoli@rmit.edu.au

RMIT University, Melbourne, 3000 VIC, Australia

CIRCLE, Lund University, Sweden

Charlie Karlsson

charlie.karlsson@ju.se

Jönköping International Business School, Sweden
Blekinge Institute of Technology, Sweden
University of Gothenburg, Gothenburg, Sweden

Papers in Innovation Studies no. 2021/1

(forthcoming in Technological Forecasting and Social Change)

The Role of Location on Complexity of Firms' Innovation Outcome

Accepted in Technological Forecasting & Social Change

Sam Tavassoli [a,b*] and **Charlie Karlsson** [c,d]

[a] Senior Lecture, School of Management, RMIT University, Melbourne, 3000 VIC, Australia
[b] Research Fellow, Centre for Innovation, Research and Competence in the Learning Economy (CIRCLE), Lund University, Lund, Sweden
[c] Professor, Jönköping International Business School, Jönköping, and Blekinge Institute of Technology, Karlskrona, Sweden
[d] Professor, Institute of Innovation and Entrepreneurship, University of Gothenburg, Gothenburg, Sweden

*Corresponding author: Sam Tavassoli: sam.tavassoli@rmit.edu.au

Abstract
In this paper we analyze how the location of firms influences their innovation outcomes, particularly the complexity of the outcomes. Using three waves of the Community Innovation Survey in Sweden for a balanced panel of firms from 2006 to 2012, we identified a range of innovation outcome categories, i.e. simple and complex (low-, medium-, highly-complex) innovation outcomes. The backbone of such categorization is based on how firms introduce a combination of Schumpeterian types of innovations (i.e. process, product, marketing, and organizational). Then we consider three regional characteristics that may affect the innovation outcomes of firms, i.e. (i) qualified labor market thickness, (ii) knowledge-intensive services thickness, and (iii) knowledge spillovers extent. We find that regional characteristics do *not* affect firms' innovation outcomes in terms of their degree of complexity ubiquitously. They are only positively associated with those firms that introduce the most complex innovation outcomes. For firms with less complex innovation outcomes, regional factors seem not to play a pivotal role. For these innovators, internal resources as well as formal collaboration with external partners have a significant role.

Keywords: innovation outcome; location, agglomeration economies; knowledge spillovers, Community Innovation Survey

JEL-Codes: D22, L20, O31, O32

Highlights

- Firms introduce a range of innovation outcome categories in terms of complexity, i.e. simple and complex (low-, medium-, highly-complex) innovation outcomes.
- Regional factors do not affect firms' innovation outcomes, in terms of their degree of complexity, ubiquitously.
- For firms with highly complex innovation outcomes, the regional factors do have a significant effect on their innovation outcomes.
- For firms with less complex innovation outcomes, the regional factors do not have a significant effect, instead, the internal resources as well as formal collaboration with external partners matter.

1. Introduction

The Resource Based View (RBV) literature argues that internal resources, such as technological knowledge and human capital, matter for innovation outcome of firms (Penrose, 1956; Wernerfeldt, 1984; Foss, 2004). More recent literature adds the importance of external sources of knowledge as well as complementarities between internal and external resources for innovation (Cassiman and Veugelers, 2006). There are two shortcomings in this stream of literature. First, when it comes to conceptualizing and operationalizing the external sources of knowledge, majority of previous studies have focused on deliberate and strategic endeavors that firms perform in order to reach to external knowledge, via for instance R&D outsourcing or company acquisition (Arora and Gambardella 1990; Ronde and Hussler, 2005)[1]. However, location-specific externalities, such as (unintentional) intra-regional knowledge spillover, which are associated with certain regional milieu, are commonly oversighted to explain innovation of firms. Accounting for such location-specific factors is pivotal according to the regional innovation system (RIS) and geography of innovation literature, because they can foster innovation, via knowledge spillover and labor matching mechanisms, even though in this case there is neither any formal nor deliberate search to acquire external knowledge (Bathelt et al, 2004; Feldman and Kogler, 2010). Second, those firms who manage to be innovative, often do not simply innovate in one type of innovation. Indeed, recent evidence from Germany and Sweden shows that majority of innovative firms engage in and successfully introduce different types of innovation simultaneously, i.e. a combination of product, process, marketing, and organizational innovations (Schubert, 2010; Karlsson and Tavassoli, 2016). This is because such simultaneous and complex engagement in variety of innovation types, hence so-called 'complex innovation outcome' pursued by firms (Le Bass and Pousing, 2014), induces amplified effect on performances (e.g. productivity) of firms (Evangelista and Vezzani, 2010; Tavassoli and Karlsson, 2016). However, our understanding about determinants of such complex innovation outcome of firms is still limited.

The purpose of this paper is to analyze how the location of firms influences the innovation outcomes of firms, particularly the complexity of their innovation outcomes. Our point of departure is that as much as complex innovation outcomes are shown to be beneficial for the performance of firms, they are more demanding in terms of access to internal and particularly

[1] In this vein, 'open innovation' literature argues that external knowledge can also come from (formal) collaborations with external partners such as suppliers, customers, competitors, universities and research institutes (Laursen and Salter, 2006).

external knowledge sources. This is because a successful introduction of more than one type of innovation requires fairly distinct but also orchestrated resource mobilizations, different types of knowledge, and even involvement and leadership of different organizational departments (OECD, 2005; Schmidt and Rammer, 2007)[2]. Therefore, a firm who engages and successfully manages to introduce a complex innovation outcome involving a variety of innovation types simultaneously, needs more external knowledge, such as location-specific knowledge sources, than a firm that does not innovate at all or involves in a simple innovation outcome (e.g. introducing only product innovation).

Our empirical investigation is based on a balanced panel of firms participated in three waves of Community Innovation Survey (CIS) in Sweden, which covers their innovation activities from 2006 to 2012. The dataset allows us to trace the innovation activities of firms and hence the extent of the complexity of their innovation outcomes in a range of spectrum, i.e. from deciding not to (or failing to) innovate at all to deciding and successfully managing a highly complex innovation outcome of having product, process, marketing, and organizational innovations simultaneously. We expect that a firm with a complex innovation outcome is nurtured better in a knowledge-rich region with higher positive agglomeration externalities, where, for instance there is a higher supply of qualified labor, higher extent of intraregional knowledge spillover, and a higher supply of specialized Knowledge-Intensive Services (KIS) in the region. This is because such regional factors acts as 'additional' inputs in firms' knowledge production function, and therefore can enhance the complexity of their innovation outcomes[3].

The rest of the paper is organized as follows: Section 2 provides theoretical background for innovation outcomes, complexity of such outcomes, and why firms are heterogeneous in terms of the complexity of their innovation outcomes. We then augment the knowledge production function to incorporate the complexity of innovation outcomes in one hand, and the regional characteristics, as an additional input to the function, on the other hand. Section 3 describes the dataset and also illustrates and discusses the frequency of various types of innovation outcomes across various regional categories in our sample of firms. Section 4 explains our empirical

[2] For example, while product innovation (as a technological innovation) requires introducing novelty in product specifications or functionalities and mainly led by R&D departments, marketing innovation (as a non-technological innovation) requires introducing novelty in marketing methods, such as packaging, product placement, promotion or pricing models, which is mainly led by marketing departments.

[3] And alternative explanation is that such regional characteristics constitute the so-called 'thick' Regional innovation System (RIS), which in turn ca affect the firms' innovation outcomes in terms of their degree of complexity.

strategies and Section 5 present the result of empirical analyses about the regional determinants of different innovation outcome categories. Section 6 concludes and provides suggestions for future research.

2. Innovation Outcomes of Firms and Their Locations

2.1. Innovation Outcome of firms and the complexity of it

Innovation outcome(s). A class perspective on innovation outcome has been to capture it through firms' patent applications/granted. This measure is often criticised to have several unsatisfactory features, for example (i) being a more indirect or intermediate measure of innovation (Comanor and Scherer, 1969; Kleinknecht et al, 2002; Smith, 2005), and (ii) the propensity to patent differs between sectors (Paci and Usai, 1999; Hipp and Grupp, 2005). Overall, it is more appropriate to consider patent as a measure of invention rather than innovation.

Community Innovation Survey (CIS) has provided a more direct measure of innovation outcome since the late 90s in Europe. For example, it provides a continuous measure capturing the amount of innovative sales of firms, which is argued to be superior compared to other commonly used indirect measures of innovation, such as patent application or R&D intensity (Kleinknecht et al, 2002; Smith, 2005). The use of such direct measures to capture a firm's innovation performance is becoming increasingly popular in empirical studies in the fields of both management and economics (Crepon et al, 1998; Cassiman and Veugelers, 2006; Lööf and Heshmati, 2006; Tavassoli, 2015). Another feature of CIS data is that it allows to go beyond the typical technological innovations (i.e. product and process innovation) as the innovation outcome, which has been classically the focus of economists (Utterback and Abernathy, 1975; Cabagnols & Le Bas, 2002; Du et al, 2007). The latter waves of survey includes non-technological innovations (i.e. market and organizational innovations) as well. This is well in line with Schumpeter (1934)'s taxonomy of innovation outcomes, which clearly distinguished between at least four types of innovation, spanning from technological to non-technological innovation outcomes.

For the purpose of this study, we use four type of innovation (out of originally five types proposed by Schumpeter), i.e. product, process, marketing, and organizational innovation These four types are directly in line with OECD (2005)'s definitions (for the exact definitions of them, see notes in Table 2).

Complex innovation outcome. Understanding the variety of innovation outcomes (beyond product innovation), dates back to at least the product/industry life cycle literature in which product and process innovations are considered as possible outcomes (Abernathy and Utterback, 1978; Klepper, 1996). According to this literature, firms *shift* from product innovation to process innovation along the stages of product/industry life cycle, as the dominant design is achieved and cost-efficiency of the process become more important than offering differentiated products. Firms may even shift to non-technological innovation as the industry decline and obsolescence (Tavassoli, 2015). However, the possibility of *simultaneous* introduction of variety of innovation outcomes has been less elaborated theoretically and understudied empirically.

As soon as we have data on variety of innovation outcomes per firm, there is a possibility to observe that some firms identify themselves to be successfully introducing more than one types of innovation outcome in a given period of time. Recent empirical evidence shows that this is indeed the case. Schubert (2010) and Karlsson and Tavassoli (2016) showed, for Germany and Sweden respectively, that majority of innovative firms engage and successfully introduce different types of innovation outcome simultaneously, i.e. a combination of product, process, marketing, and organizational innovations. This means majority of firms introduce more complex innovation outcome portfolio than previously thought, hence so-called "complex innovation outcome" (Le Bass and Pousing, 2014; Tavassoli and Karlsson, 2016). Even if complex innovation outcome is more demanding in compare with aiming for a simple innovation outcome (e.g. only product innovation), firms still decide to pursue such simultaneous engagement in variety of innovation types because it has positive and synergic effect on their performances (Evangelista and Vezzani, 2010; Hervas-Oliver et al, 2015; Tavassoli and Karlsson, 2016)[4].

Today there is a large body of research on the determinants of innovation at the level of firms, industries, regions and nations (Dosi, 1988; Cohen, 2010; Klepper, 1996; Tavassoli, 2015). However, surprisingly little is known theoretically and empirically about the determinants of firms' innovation outcome for those firms who manage to introduce complex innovation outcomes. Although recent studies attempt to explore the determinants of such complex innovation outcomes (Du et al, 2007; Schubert, 2010; Kalrsson & Tavassoli, 2016), the external

[4] We will provide the detailed and empirical explanation on how to capture the complexity level of innovation outcome in Section 4.

determinants, particularly related to regional factors in which a given firm is located is understudied.

Why complex innovation outcome. There are three reasons for why the complex innovation outcome matters for firms, and hence worthy of study. First, it is based on the logic of 'capturing the value'. Teece (2010) argues that product (goods or services) innovations by themselves may create a value but not necessarily capture the value for the firm. Following this argument, we elaborate on a mechanism in which firms create and capture value *through* engaging in multiple types of innovation outcomes simultaneously, as follows. Firms compete in different markets, and in each market firms that are best at providing value added through differentiated products (product innovation) enjoy relatively higher profits than non-innovative firms. Now if a product innovator combines its differentiated products with novelty in marketing methods that reinforce the customers' willingness to pay for such differentiated products (marketing innovation), then it can have even higher profit. On top of it, if such product and marketing innovator can simultaneously improve the supply chain efficiency by reducing the production and delivery costs (process innovation), it can enjoy even higher profit. And finally, if such product-marketing-process innovator, which is already a complex innovator, can even add novelty into its internal organizational routine, such as knowledge management system, and its existing external strategic alliances (organizational innovation), it can maintain and capitalize its accumulated knowledge internally and externally in a long-run sustainably, reinforcing its already complex and successful innovation outcome portfolio even further. This firm is an example of a highly complex innovator and is expected to enjoy relatively higher profits and performance in general in compare with non-innovators as well as other innovators who are not as complex innovator as the firm in question (Teece, 1986; Tavassoli and Bengtsson, 2018).

Second, it is based on 'complementarity effect' between different types of innovation outcomes (Schmidt and Rammer, 2007; Schubert, 2010). Product innovations may induce organisational innovations, for example when a new product require the establishment of new production or sales divisions, hence calling for a new re-organisation of work flows or knowledge management (Medrano and Olarte-Pascual, 2016). Product innovations are also often closely associated with marketing innovations (Bartoloni and Baussola, 2016). A new product may demand new methods of marketing, such as pricing or promotion channels. Process innovation can be also closely linked to non-technological innovations. For example it can go hand to hand with organizational as well as marketing innovation, since introducing new technologies in production or distribution may demand reorganising business routines, which may trigger the introduction of new business practices, or it can result in new marketing approaches in order to maximise the profit from increased production capacities (Damanpour and Aravind, 2012). Such complementarity effect between different types of innovation outcomes can in turn lead to amplified effect on firm performance in terms of sales and productivity growth. Accordingly, Tavassoli and Karlsson (2016) empirically showed that the more complex innovation outcomes firms have, the higher productivity of the firms, particularly if there is a balance between technological and non-technological innovations. Moreover, such complex innovation outcomes help firms with a lack of certain technological capabilities (e.g. R&D) to overcome that weakness (Hervas-Oliver et al, 2015).

And third, having a complex innovation outcome portfolio creates an 'isolating mechanisms' against replication by competitors (Teece, 2010). It is much harder to replicate innovation outcomes of a firm, if such firm has simultaneous introduction of not only a novel product, but also for example compatible organizational change in knowledge management that goes in tandem with development of such novel product plus even a novel marketing method that enhance willingness to pay of current and future customers for that novel product. This way firms can develop competitive advantage by not only development of resources but also from the capability to integrate them in a unique way (Ennen and Richter, 2010).

2.2. Location of firms and Complexity of Innovation Outcomes

Following the classic knowledge production function (Griliches, 1979; Crépon, Dueget & Mairesse, 1998) or rather in our case an innovation production function, the innovation outcome(s) of firms can be formulated as follows:

$$Q_{ij} = H_i^{\alpha} I_i^{\omega} E_i^{\gamma} R_i^{\partial} \qquad (1)$$

Where Q_{ij} is a vector representing the innovation outcome(s) j for firm i. The H_i is the human capital input in innovation activities in firm i , I_i represents internal innovation inputs in firm i, such as internal R&D investment or investment in acquisition of machineries, E_i represents external sources of innovation inputs in firm i (excluding regional factors), such as formal and intentional collaborations with external partners like supplier and customer. H_i and K_i are theoretically based on RBV broadly speaking (Foss, 2004), while E_i is motivated by open innovation literature (Laursen and Salter, 2006). Finally, R_i represents innovation inputs spilling over to the firm i from the hosting region in which firm i is located. R_i is theoretically based on geography of innovation, among other literature (Feldman, 1994, Porter and Stern, 2001; Feldman and Kogler, 2010). The parameters α, ω, γ and ∂ are all positive, and their values can be smaller, equal to or larger than 1, which implies that we can have decreasing, constant or increasing returns to scale.

Most empirical studies have focused on product innovation as the innovation outcome, but the innovation production function is equally applicable when it comes to other types of innovation outcome as well as the complexity of innovation outcomes. This point is demonstrated by Schmidt and Rammer (2007) who found out that the determinants of various technological (product and process) and non-technological (marketing and organizational) innovations are almost identical.

The external regional innovation inputs, R_i, are included in the Equation (1) to specifically account for possible agglomeration externalities effects from the firm's regional economic milieu (Camagni and Capello, 2002; McCann and Folta, 2008). Even if firms significantly invest in internal R&D and internal competencies and capabilities, it is of fundamental importance for them to search externally for novel ideas, knowledge and technology and to closely watch the behavior of competitors (Porter and Stern, 2001). The external innovation inputs may be substitutes for the firm's own human capital and internal innovation inputs and can thus make innovation less costly. However, they may also be complements to the firm's own human capital and innovation inputs and thus boost the innovation output of the firm at a given cost level (Arora & Gambardella, 1990; Cassiman & Veugelers, 2006) as well as lead to more advanced innovations.

We identify and elaborate three crucial external regional inputs, R_i, capturing the agglomeration externalities effect. These regional inputs are labor market thickness, specialized service thickness, and the extent of knowledge generation and spillover in the region[5]. The choice of our external regional factors is in line with Localization or Marshallian externalities (McCann & Folta, 2008). First, the labor market thickness provides both supply and demand conditions necessary for innovation (Feldman and Tavassoli, 2015). Starting from the supply side, regions differ in terms of the size of their labor supply and also the diversity of their labor forces in terms of education and experience (Porter and Stern, 2001). Large and dense urban regions tend

[5] There are other regional factors that we do not explicitly take into account in this paper. For example, effective institutions in regions, which can bring down transaction costs and thus the costs associated with innovation. They increase the incentives to innovate through their definition and protection of intellectual property rights. Effective institutions offer the foundations for open innovation by facilitating knowledge flows and the appropriation of the rents from innovation.

to attract more creative and skilled people, i.e. they have thicker labor market (Landry, 2008). Such thick labor market is particularly supportive for innovation, since it makes the labor matching easier for firms, by facilitating the recruitment of the specialized skills needed for specialized tasks in innovation processes (Coles and Smith, 1996; McGuirk and Jordan, 2012). Innovating firms get lower innovation costs in thick labor markets since it is easier for them to recruit exactly the right kinds of skilled and specialized labor in such labor markets (Krugman, 1993; Feldman, 1994). The better labor market matching in thick labor markets tend to make innovators in these regions more productive and more innovative, which tends to result in higher profits, making it easier for firms to finance continuous innovation. Finally, there is a reinforcing *feedback loop* mechanism in thick labor markets that is beneficial for innovating firms. Once a thick labor market attracted talented and skilled people, residing firms in the region will have higher innovation outcome and hence higher productivity (Lööf and Heshmati, 2006). Such higher productivity, in turn, makes it easier for these firms to pay higher salaries, which encourages their skilled labors to stay for the longer time and also attract additional skilled labors from other regions to move into the thick labor market, hence making the labor market even thicker and the residing firms more innovative (Antonelli et al., 2013).

Apart from supply of labor, a thick labor markets provides favorable demand conditions for innovation all outcomes (Porter and Stern, 2001). Specifically, they offer an advantage for innovation by providing firms with proximity to a concentration of demanding customers, who can be exiting customers, potential future customers, and more importantly early-adopter customers. They also offer a positive information externality, since economic agents may receive signals about the strength and the composition of the regional demand by observing the successful or unsuccessful trade of competitors. The qualified and demanding customers are mainly to be found in a large and dense urban regions (Brunow and Miersch, 2015), which is an important prerequisite for successful innovation, both technological (e.g. product innovation), but also non-technological (e.g. marketing) innovation outcomes.

Second, the supply specialized service thickness in a region provides an important necessary condition for innovation, based on geography of innovation theory (Feldman, 1994; Feldman and Kogler, 2010). Regions differ substantially in their supply of non-traded inputs, i.e. in terms of their service infrastructure and particularly their supply of knowledge-intensive business services. Such inputs are provided both in greater variety and at lower costs in large urban regions (Coles and Smith, 1996), which stimulates innovation (Krugman, 1991 a & b). This argument is in line with the notion of *nursery cities*, in which large and diversified cities with specialized services facilitate the prototyping and try and error for firms' product development as well as their non-technological innovation (Duranton and Puga, 2001). Thicker regions in terms of specialized services also offer a more developed physical infrastructure in terms of public transport and access to major highways and airports, which offer benefits to innovators in the form of higher accessibility to intra and interregional knowledge flow. These knowledge flow can function as a nucleus of uncountable networks of various types with a spatial scale ranging from the very local to global, which are a prerequisite for innovation (Nijkamp, 2003). Thus, an economic milieu with thick specialized services providing 'extra' knowledge inputs as well as knowledge infrastructure for its residing firms, hence increases the chance that firms successfully managed to not only innovative but also successfully innovative in variety of innovation types, both technological and non-technological ones, simultaneously.

And third, a higher extent of knowledge production and consequently knowledge spillover in a region provides an important condition necessary for innovation, based on knowledge spillover theory (Acs et al, 2009; Funk, 2014). Regions vary substantially regarding the volume and types of novel ideas, knowledge and technology that they generate due to a varying presence of research universities, research institutes, innovating firms, and so on, i.e. organizations that are direct or indirect generators of innovation (Acs, 2000). They also differ in terms of their knowledge and commercial linkages to other regions, for example through large international airport, which facilitates inflow of knowledge embodied in people. An important characteristics of a knowledge generating region is the existence of intra-regional geographically-bounded knowledge spillover (Jaffe et al, 1993; Funk, 2014). The knowledge spillover happens because the 'knowledge generator organizations' cannot fully exploit their own generated knowledge, which itself is due to the so-called knowledge filters within those organizations. The source of such knowledge that spills over to third party agents in the region, i.e. knowledge spillover generators, are identified to be innovative and research intensive organizations (Audretsch and Keilbach, 2007). Firms that are located in regions with higher extent of knowledge spillover tend to be more innovative, either through learning or sorting, i.e. they draw on or adapt to the urban economic milieu (Doloreux and Parto, 2005). Thus, an economic milieu with many innovative firms can increase the probability that firms located in such regions are also innovative, since such locations offer firms an informational externality through the observation of different innovating firms' successful and unsuccessful attempts to innovate (Camagni and Capello, 2002).

To sum up, firms rely on their internal resources and external formal knowledge sources (such as collaboration with external partners) to be innovative (Foss, 2004; Laursen and Salter, 2006). But to be a more complex innovator, we argue that firms need more in terms of the inputs in their innovation production function. One possible source of such 'extra' input to firm's innovation production function is the positive agglomeration economies, which attributes to the regional milieu in which the firm is located. We then elaborated on three prominent sources of the agglomeration economies, i.e. regional labor market thickness, specialized business services thickness, and intra-regional knowledge spillover. Such regional factors provide extra innovation inputs for firms in the form of ideas, information, knowledge and/or technologies, which spills over into residing firms in the region. They also facilitated the labor matching for specialized task required in innovation processes. This in turn can foster the development of *both* technological and non-technological innovations of firms (Iansiti and Levien, 2004)[6]. Moreover, because firms inherently have motives to be complex innovators than a simple innovator, based on three mechanism we elaborated on section 2.1, we expect that agglomeration economies, as the extra input to firms' innovation production function, induces firms to successfully introduce innovation outcomes simultaneously, i.e. becoming a more highly-complex innovators. This is proposed as the below hypotheses, where Hypothesis 1 is our base hypothesis and hypothesis 2 is our main hypothesis.

Hypothesis 1: *The probability that a firm introduces an innovation outcome increases with the thickness of the regional labor market, the thickness of the regional specialized producer services, and the intra-regional knowledge spillovers.*

Hypothesis 2: *The probability that a firm introduces a complex innovation outcome increases with the thickness of the regional labor market, the thickness of the regional specialized producer services, and the intra-regional knowledge spillovers.*

3. Data

3.1. Dataset

The innovation related data in this study comes from three waves of the Swedish Community Innovation Survey (CIS) in 2008, 2010, and 2012. The CIS 2008 covers the period 2006-2008 and CIS 2010 covers the period 2008-2010 and so on, hence using the three waves, provide us

[6] Here, we do not discriminate between technological (product and process) and non-technological (marketing and organizational) innovations, mainly because the (firm-level) determinants of them are shown to be fairly similar (Schmidt and Rammer, 2007).

with information about innovation activities of firms over a seven years period, i.e. from 2006 to 2012 inclusively. We chose 2008 as the start of the analysis, since this year is the earliest and the first time that CIS survey has information concerning the four types of Schumpeterian innovation (i.e. product, process, marketing and organizational), hence allowing us to construct our innovation outcome variables based on the complexity of the outcomes. The survey consists of a nearly representative sample of innovation active firms in industry and service sectors with 10 and more employees. Among them, the stratum with 10-249 employees has a stratified random sampling with optimal allocations and the stratum with 250 and more employees is fully covered. The response rates in the three waves vary between 63% and 86%, in which the later CIS waves having higher response rates compared with the earlier ones.

We construct balanced panel dataset of firms consists of 1722 observations, corresponding to 574 firms who participated in all three waves of CIS. This is thanks to the unique identifier number each participating firm is allocated in each wave of the CIS by the Statistic Sweden (SCB). Then we merged the innovation-related data with other firm-characteristics data (e.g. export, import, ownership structure) coming from registered firm-level data maintained by the SCB. This provides us with an extensive set of control variables capturing both internal and also external (such as collaboration with external partners) sources of knowledge for the firms. Finally we regionalize each firm in the database into one of the 72 Local Labor Market Areas (or functional regions) to which each firm is located in Sweden. The description of all variables used in our dataset is presented in the Appendix 1. The Vector Inflation Factor (VIF) among regressors has the mean value of 2.21 and each variable get a VIF score of below 3.4. This implies that multicollinearity is rather mild among our variables and may not bias the subsequent regression analyses results in Section 5.

3.2. Variables and descriptive statistics

Dependent variable. Our dependent variable is the *Innovation Outcomes* (*IOs*) of firms, which is a categorial variable. We operationalize the *IOs* by capturing the 'complexity' of it, i.e. to what extent firms manage to successfully introduce one or more types of Schumpeterian innovations, i.e. product, process, marketing, and organizational innovation[7]. In our dataset, a

[7] According to OECD (2005), a *product innovation* is the market introduction of a new or significantly improved good or service with respect to its capabilities, user friendliness, components or sub-systems. Product innovations (new or improved) must be new to the enterprise, but they do not need to be new to the market. A *process innovation* is the implementation of a new or significantly improved production process, distribution method, or support activity for goods or services, such as maintenance systems or operations for purchasing, accounting, or computing (exclude purely organizational innovation). Process innovations must be new to the enterprise, but they

given firm at a given point in time can declare to have been able to introduce one of these four types, any combination of these four types simultaneously, or none them at all. Altogether, a given firm can have any of the sixteen-possible combination of such four innovation types at a given point in time. Following Schubert (2010) and Karlsson and Tavassoli (2016), we group such sixteen combinations into five *categories*, which we call them *Innovation Outcomes (IO)*, ranging from Non-Innovation Outcome to Highly Complex Innovation Outcomes. Specifically, first of all, if a firm does not innovate at all in a given period *t*, then it is considered as having *NON IO* as the based (reference) category. Second, if a firm introduces 1 type of innovation outcome (e.g. product innovation), then it falls under the category of so-called *SIMPLE IO*. Third, if a firm introduces 2 types of innovation outcomes simultaneously (e.g. product and process innovation), then then it falls under the category of so-called *COMPLEX_LOW IO*. Third, if a firm *i* introduces 3 types of innovation outcomes simultaneously (e.g. product, process, and marketing innovation), then it falls under the category of so-called *COMPLEX_MEDIUM IO*. And finally, if a firm introduces all 4 types of innovation outcomes at the same time (i.e. product, process, marketing, and organizational innovations), then it falls under the category of so-called *COMPLEX _HIGH IO*. These are five mutually exclusive categories capturing the complexity of innovation outcomes of firms.

Explanatory variables. We have three explanatory variables, corresponding to Labor Market Thickness, Specialized Supplier Thickness, and Knowledge Spillover extent. These three variables refer to the R_i in the Equation 1. The choice and measurement of the three regional variables are based on Tavassoli and Karlsson (2017), among others. Labor Market Thickness is measured as the total number of employees with at least three years of university education in functional region *r* in year *t* minus firm *i*'s employment (log). The Specialized Supplier Thickness is measured as the number of employees in Knowledge Intensive Service (KIS) sector in functional region *r* in year t minus firm *i*'s employment located in region *r*, if firm *i* is in KIS sector itself (log). And the Knowledge Spillover is measured as the number of innovative

---

do not need to be new to your market. A *marketing innovation* is the implementation of a new marketing concept or strategy that differs significantly from the enterprise's existing marketing methods and which has not been used before. It requires significant changes in product design or packaging, product placement, product promotion or pricing. It excludes seasonal, regular and other routine changes in marketing methods. An *organizational innovation* is a new organizational method in the enterprise's business practices (including knowledge management), workplace organization and decision making, or external relations that has not been previously used by the enterprise. It must be the result of strategic decisions taken by management. It excludes mergers or acquisitions, even if for the first time.

firms[8] in functional region r in year t minus firm i located in region r, if firm i is innovative itself[9].

Control variables. We have a wide range of control variables, which are preliminary an extensive set of firm-level characteristics. These variables capture internal resources of firms (such as the internal R&D investments, human capital and physical capital of firms), as well as external formal knowledge linkages of firms (mainly through collaboration with external partners, such as customer or suppliers). We also have the usual firm-level characteristics variables, such as size, ownership structure, international linkages through import and export, and industry sectors of the firms. Needless to say, it is essential to control for these variables in order to delineate the role of regional characteristics, while holding internal resources, formal external knowledge linkages, and usual firm level characteristics constant.

Table 1 shows the descriptive statistics for all explanatory and control variables (we will provide detailed descriptive statistics of dependent variables in the next section 3.3). The exact definitions of all variables are reported in the Appendix 1.

[Table 1 about here]

3.3. Variety of Innovation Outcomes

Table 2 reports the frequency and percentage of each innovation outcome categories. It shows that firms introduce a wide varieties of innovation outcome categories, in terms of the complexity of the outcome. First of all, 35% of firms do not engage in any innovation, hence categorized as Non-Innovators, while the rest (65%) are innovative firms and successfully introduce a range of innovation outcome categories. Among the sample of innovative firms, there is a decreasing trend from simple to highly complex innovation outcomes, i.e. 34% chose Simple Innovation Outcome (SIMPLE IO), 30% chose Complex-Low IO, 21% Complex-Medium IO, and 15% Complex-High IO. Such a decreasing trend is not surprising for two reasons. First, it takes high physical and human capital requirements as well as managerial commitment to make a firm being engaged and successfully introduce a Complex IO toward the higher end of its spectrum. Second, in the modern highly specialized economic divisions, a

[8] An innovative firm is identified if it introduces any of the four Schumpeterian innovation outputs (product, process, organizational, and marketing innovation) in year t.
[9] Unlike labor market thickness and supplier thickness, we avoid log-transforming the knowledge spillover variable, since it has considerable zero value and also it is already fairly distributed normally.

firm may only focus on a few areas of economic activities (and thus innovations) and outsource the other needs. For example, Apple's assembling work is done by Foxconn, and thus it is Foxconn, rather than Apple, that may innovate the organizational structure of thousands of manufacturing-workers in Asia to assemble iPhones (i.e. non-technical innovations). Nevertheless, despite the capital-intensity argument as well as economic division argument, there are a good portion of innovators in our sample who are complex innovators.

[Table 2 about here]

3.4. Variety of Innovation Outcomes across various regions

Once we observe that firms are very heterogeneous in terms of their IOs categories, then the next question is what factors can explain such heterogeneity. As discussed earlier, previous studies mainly focused on firm-level factors to explain it. In addition to that, we mainly want to highlight whether regional factors can also explain part of such heterogeneity. To do so, we start with depicting how firms with different IOs are distributed in different regions in terms of regional factors, such as Labor Market Thickness, Specialized Supplier Thickness, and the extent of intra-regional Knowledge Spillovers. This is shown in the Figure 1.

[Figure 1 about here]

Figure 1 shows several noteworthy points. First, the agglomeration economies of regions seem to be constant for regions hosting firms with No-Innovation, Simple IO, and even Low-Complex IO. In particular, the level of labor market thickness, supplier's thickness, and the knowledge spillovers is almost equal in regions hosting firms with No-Innovation, Simple IO, and even Low-Complex IO. Second, there is an upward trend in agglomeration economies of regions hosting firms with complex innovation outcomes, which increases in tandem with the complexity of the outcomes. In particular, the mean values of the three regional factors increase from 5, 7, and 30 for regions hosting firms with Low-Complex IOs to mean values of 9, 12, and 42 for regions hosting firms with Complex-High IOs. Third, the sharpest increase in the mean value of regional characteristics happens for regions hosting firms with Complex-High IOs. This is particularly true for the extent of potential Knowledge Spillovers. This is already an indication that there seems to be at least a positive correlation between the thickness/extent of regional factors and the complexity of Innovation Outcomes of firms. Regions with thicker labor market, specialized service suppliers and higher extent of potential intra-regional knowledge seem to stimulate their residing firms to successfully manage and introduce a more complex innovation outcomes. The next question is whether such an initial indication is systematic or not when accounting for a wide range of firm-level characteristics.

4. Empirical Strategy

In the previous section, we descriptively showed firms choose variety of innovation outcomes in terms of complexity. But what determines such heterogeneous outcomes? While previous research shows that it is mainly driven by some firm-level characteristics (Schubert, 2010, Karlsson and Tavassoli, 2016), we add to this body of the literature that regional factors matter too. We have employed Multinomial Logit model to investigate the determinants of the various innovation outcome categories that firms successfully introduce[10]. Multinomial Logit model is a valid estimator in our empirical context, since the assumption of Independence for Irrelevant Alternatives (IIA) is not violated[11]. The probability that firm i introduces innovation outcome in the category j is given by:

$$P_{ij} = Prob(Y_i = j \,|\boldsymbol{X}_i) = \frac{\exp(\boldsymbol{X}_i'\boldsymbol{\beta}_j)}{1 + \sum_{k=1}^{J}\exp(\boldsymbol{X}_i'\boldsymbol{\beta}_k)} \qquad j = 0, 1, 2, 3, 4 \tag{2}$$

Where $\boldsymbol{X}_i$ is the vector of explanatory variables which are alternative-invariant regressors. The $\boldsymbol{X}_i$ itself composed of four subsets of variables, $H_i, I_i, E_i,$ and R_i, as elaborated earlier in the innovation production function in the Equation (1). The main explanatory variables in this study belong to the subset of R_i, capturing the agglomeration economies (regional factors) corresponding to three specific regional characteristics, i.e. Labor Market Thickness, Specialized Supplier Thickness, and the extent of potential Knowledge Spillovers (See Appendix 1 for exact definitions). The rest of variables serve as control variables in this study, as explained in Section 3.2. The $\boldsymbol{\beta}_j$ is the vector of parameters to be estimated, composed of α, ω, γ and ∂ in the Equation (1), which are a set of four parameters per each explanatory variable, capturing the effect of each variables on the probabilities of introducing each category of

[10] We have an empirical setting in which firm i can 'choose' between any of five innovation outcomes j, which are collectively exhaustive and mutually exclusive choices ($\sum_{j=0}^{J} P_{ij} = 1$). We only have alternative-invariant (case-specific) regressors, while we do not have any alternative-specific regressors. In this setting, a suitable model to employ for estimation is Multinomial Logit.

[11] IIA assumption states that characteristics of one particular choice alternative do not impact the relative probabilities of choosing other alternatives. For example, if IIA is valid, how a firm i chooses between introducing only product innovation or only process innovation ($P_{i,j=1}/P_{i,j=2}$) is independent of any other possible choices of innovation outcomes. Even though a firm's choice of a more complex innovation combination might dependent on its possible achievement of a basic innovation outcome, as we noted in Section 2.1, the formal statistical test of IIA shows that at the aggregate level of sample of firms, this assumption is met.

innovation outcomes. Finally, j is the category of innovation outcomes: j=0 to j=4, which when firms fall under the category of no innovation to the most complex innovation outcomes, as expend in section 3.2. All right-hand side variables are lagged one period of time in the subsequent analysis, in order to deal with issues of reverse causality.

5. Results

The results of our empirical estimations are presented in Tables 3, 4 and 5. These three tables are identical with the difference that each table have one of our three regional characteristics. We avoided to insert all three regional characteristics in on model (table) due to high correlations between these three regional characteristics (See the correlation matrix in Appendix 2). All firms (including non-innovative and innovative) are used in the estimations. The base model is the specific innovation outcome that firms decided not/failed to innovate at all (*NON-INNOV*). Therefore, the results in the following three tables present the determinants of the remaining four choices of innovation outcome (J=1, 2, ...4). The tables report the Relative Risk Ration (RRR)[12] of the estimated parameters and they should be interpreted with reference to the base model.

We start with presenting the estimation of the determinants of innovation outcomes of firms, including Labor Market Thickness as the regional characteristic, alongside with a range of firm-level determinants. This is reported in the Table 3.

[Table 3 about here]

The results in Table 3 show some interesting patterns. First of all, the thickness of labor markets - our first regional characteristics - does not significantly affect firms to successfully manage to introduce any of innovation outcome categories, *except* for becoming Highly-Complex innovators. Specifically, one unit increase in the thickness of the labor market in a region is associated with higher probability by a factor of 1.148 that a firm in that region becomes a Highly-Complex innovator, relative to be a non-innovator (as the base category). The interesting point is that this regional characteristic seems to be critical for firms' ability to successfully introduce not just any type of innovation outcome, but the very high end of its

[12] In Multinomial Logit Regression, it is more intuitive to interpretive the RRR than the raw coefficient. The RRR is obtained by exponentiating the multinomial logit coefficients.

spectrum in terms of complexity, i.e. combining all types of Schumpeterian innovation types simultaneously.

In addition to the regional characteristics discussed, there are also a range of firm-level characteristics that determines the complexity of innovation outcomes among firms. Interestingly enough, these factors are mainly external factors as well. First, the amount of export intensity of the firms, as an indication of *external* linkage of firms to export market and hence the backbone of the Learning-By-Exporting mechanism, matters for more complex innovation outcome categories rather than simple innovation outcome (although at 10% significance level). Moreover, the magnitude of its explanatory effect increase as the complexity of innovation outcomes increases. One unit increase in export intensity is associated with higher probability that a given firm falls under the Low-, Medium-, and High-Complex Innovation Outcomes by the factor of 1.66, 1.78, and 2.01 times, respectively, relative to fall under the non-innovative category. Second, the collaboration with external partner, particularly with supplier, shows again its explanatory effect in more complex innovation outcome categories. Firms collaborating in their innovation project with their suppliers have higher probability to fall under the Medium- and High-Complex Innovation Outcomes by the factor of 1.57 and 1.97 times, respectively, relative to fall under the non-innovative category. Third, the size of the firm also influences the complexity of innovation outcomes. One unit increase in log of the size of a given firm is associated with higher probability that a given firm falls under the Simple, Low-, Medium-, and High-Complex Innovation Outcomes by the factor of 1.13, 1.345, 1.584, 1.88 times, respectively, relative to fall under the non-innovative category. And finally fourth, the sector of the firms also determines the complexity of innovation outcomes. Being a manufacturing (as opposed to be a service) firm is associated with higher probability that a given firm falls under the Simple, Low-, Medium-, and High-Complex Innovation Outcomes by the factor of 1.40, 1.42, 2.35, 4.20 times, respectively, relative to fall under the non-innovative category.

Another interesting results concerns the internal R&D investment, which is positively associated with the probability of firms to fall under most of innovation outcome categories relative to be non-innovative. However, interestingly, it does not contribute to explain the Highly-Complex IO. It seems for firms that made it to have a Highly-Complex IO, the role of internal R&D fades away and it is the external factors, among others the regional characteristic

Labor Market Thickness, which significantly matters for innovation outcome among these highly complex innovators.

Table 4 and 5 report the estimation of the determinants of innovation outcomes of firms in line with Table 3. The difference is that instead of Labor Market Thickness, we included Specialized Supplier Thickness and the Knowledge Spillovers variables in the Table 4 and 5, respectively. This way, we can shed light on the possible explanatory power of another two regional characteristics on the innovation outcomes categories of firms.

[Table 4 about here]

[Table 5 about here]

The results in Table 4 and 5 are similar to those in Table 3. Both of the regional characteristic variables are only significant for the Highest Complex innovation outcome of firms, i.e. in Models (4') and (4''). When it comes to the magnitude of the effect, one unit increase in the thickness of the specialized service in a region is associated with higher probability by a factor of 1.001 that a firm in that region becomes a Highly-Complex innovator, relative to be a non-innovator. The magnitude is higher for the knowledge spillover variable. One unit increase in the number of innovative firms in the region (a proxy for knowledge spillover) is associated with higher probability by a factor of 1.012 that a firm in that region becomes a Highly-Complex innovator, relative to be a non-innovator. This, again, shows that the characteristics of the region where a firm is located, here captured as Specialized Supplier Thickness and Knowledge Spillover extent, indeed favor firms to not only become innovative but also a very complex innovative one. The results concerning the firm-level characteristics (internal and external variables) are mainly consistent with the literature and the above discussion of the results in the Table 3. All in all, we can confirm our main hypothesis 2, while we only partly can confirm our base hypothesis 1.

6. Conclusion

6.1. Brief summary of aim and results

Already Schumpeter (1934) distinguish between four different basic types of innovation, i.e. product, process, marketing and organizational innovations. Recent evidence suggest that a sub-sample of firms engage and successfully introduce a *combination* of these four basic types, i.e. firms are not only innovating, but also innovating with 'complex' innovation outcomes

(Schubert, 2010; Le Bass and Pousing, 2014; Karlsson and Tavassoli, 2016). While previous research shows that firm-level factors can partly explain the variation in heterogeneity of firms' innovation outcomes and the complexity of such outcomes, we went beyond such argument by incorporating regional factors, as an additional input to knowledge production function, as well.

The main findings reinforce the idea that location matters for innovation (Feldman, 1994; Porter and Stern, 2001; Feldman and Kogler, 2010), and particularly for the complexity of innovation outcomes. First, based on descriptive statistics, we find that there seems to be at least a positive correlation between the thickness/extent of regional factors and the complexity of innovation outcomes of residing firms. In other words, regions with higher positive agglomeration externalities, through knowledge spillover and labor matching mechanisms, seem to nurture firms' ability to engage and successfully introduce a Highly-Complex innovation outcome. Then we investigated such initial indication systematically by accounting for a wide range of firm-level characteristics (both internal and external factors) and employing Multinomial Logit regressions in order to model the category of innovation outcomes of firms, in terms of their complexity. We affirmed that certain regional factors significantly affect the choice for firms to be complex innovators. These regional factors are: labor market thickness, (ii) specialized supplier thickness, and (iii) the extent of intra-regional knowledge spillover occurring in the region. Interestingly, our findings highlight that typical favourable regional factors (i.e. thickness of Regional innovation System) do not affect firms' innovation outcomes in terms of their degree of complexity ubiquitously. Such commonly perceived favourable regional factors are positively associated with *only* those firms with the most complex innovation outcomes (and not the rest of the firms). For firms with less complex innovation outcomes, regional factors seem not to play a pivotal role. For these innovators, the 'usual suspects' factors such as internal resources and investment as well as formal collaboration with external partners have a significant role.

6.2. Contribution to literature

The findings in this paper has contribution to the literature on innovation studies in general and geography of innovation and Regional Innovation System (RIS) in particular. Even though the literature is fairly rich (Feldman, 1994; Doloreux and Gomez, 2017), however, the literature gives very little guidance concerning how to nurture regional clusters of highly complex innovators, since (i) it has been mainly dominated by explaining *regional* variation of *intermediate* measure of innovative activities, such as patent application (Jaffe et al, 1993;

Porter and Stern, 2001; Ronde and Hussler, 2005; Tavassoli and Carbonara, 2014; Castaldi at al, 2015), hence commonly does not capture direct measure of innovation output, (ii) it has underplayed the primary role of the firm as a key actor of knowledge development and innovation (Marques & Morgan, 2018). Recent studies attempted to capture a more *direct* measure of innovation outcome at the level of *firm*, however, with sole attention to technological innovation, particularly product innovation (Love and Roper, 2001), leaving the analysis of 'complexity' of innovation outcomes for firms, beyond the typical product innovation, understudied. Therefore, there has been a lack of *systematic* understanding of why *firms* located in different regions show heterogeneity in their *complexity* of innovation *outcomes*.

In this paper, we contribute to the literature by identifying three major regional factors that systematically influence the complexity innovation outcomes at the level of firms (cf. McCann and Folta, 2008). Our approach mainly relates to Thick Diversified RIS, while it also incorporates elements of Thick specialized RIS (Isaksen et al, 2018). Moreover, we also empirically contribute to the RIS literature by, firstly, proving a large scale and systematic firm-level evidence. Majority of not only classic (e.g. Cooke & Morgan, 1994) but also recent RIS literature (Lew et al, 2018; Pinto, & Fernández-Esquinas, 2018) have case-study based approach. Even though insightful about the influence of actors and dynamics of RIS in those cases, the ability for generalization in these studies has been limited. Secondly, our study measures innovation directly through various innovation outputs such as product innovation (as opposed to intermediary outputs, such as R&D investment and patent applications). Thirdly, it measures the 'degree of complexity' of innovation outcomes of firms by a simple, yet novel measure based on various combinations of Schumpeterian innovation types. And finally, our study controls for an extensive firm level factors, allowing to isolate the effect of regional factors on firm-level innovation outcomes located in a given region. While we cannot discriminate between our three regional explanatory variables since they are highly correlated, nevertheless, our results illustrate that positive agglomeration economies are important for firms who want to pursue a highly complex innovation outcomes.

6.3. Implication for policy and practice

Our paper also has several important implications for innovation policy in general, and specifically on regional innovation policy. Let us start with the an important and emerging observation: there seems to be a subsample of firms that are highly complex innovators. In our sample, they amount to 10% of the total sample and 15% of innovative firms' sample. These star-level innovators form a minority, but they are the ones that do the hard job and successfully introduce both technological and nontechnological innovation simultaneously. Due to synergic effect of having such complex innovation outcome, these firms are the best in terms of performance such as productivity, and also in terms of long-run comparative advantage (Hervas-Oliver et al, 2015; Tavassoli and Karlsson, 2016). Therefore, it is important to understand what regional environments and regional innovation policies that can nurture this relatively small but influential subsample of innovative firms. Our results show that regions with higher positive agglomeration economies are the favourable regions for nurturing these firms.

The next question is what regional innovation policies mix (Magro & Wilson, 2019) can enhance agglomeration economies and hence can nurture and maintain existing highly complex innovators and to stimulate more firms to become such innovators. First of all, regional innovation policies can be classified into two core types (Nauwelaers & Wintjes, 2003): (i) system-oriented policies, which principally concern network-building and brokering, cluster development, innovation system-development, cooperation and mobility, and (ii) firm-oriented or actor-based policies, which principally concern the human, financial and/or physical capital and e.g. business support and advice. We argue that regional innovation policy-makers need to find an optimal combination of the two types given the region-specific agglomeration economies in each region. Therefore, regional innovation policies must draw on the place-based agenda (Barca, 2009) and thus need to be tailored to each specific region and its specific conditions, which reduces the relevance of "best-practice models" for such policies (Martin & Trippl, 2014).

Second, innovative firms (particularly highly complex innovators) are critically dependent upon inputs from other regions in terms of ideas, knowledge and innovative inputs that are not available in the home region (Strambach & Klement, 2012)[13]. In order to provide fine-tuned recommendations for regional innovation policy in regions with cluster of such innovators, it is crucial to help innovative firms preserving and extending networks to other regions, notably by improving interregional transportation and communication links (Karlsson & Manduchi, 2001).

[13] This is in line with the notion of *combinatorial knowledge dynamics*, i.e. involvement of a variety of innovation actors belonging to different technological, sectoral, organizational and spatial contexts (Strambach & Klement, 2012), through their intra-regional and particularly inter-regional innovation networks (Huggins & Thompson, 2017).

Regional innovation policies also need to extend and develop the locally structured intra-regional innovation networks notably between innovative firms and universities to improve technology transfer from universities to innovative firms but also to stimulate interactive learning among innovative firms and other innovation actors, such as knowledge-intensive service firms (Brown, 2016).

Third, regional innovation policies must ensure sufficient absorptive capacity and human capital within the regional base of innovative firms, since high quality human capital is critical for the performance of innovative firms (Fritsch & Schindele, 2011). In order to do so, policy makers may consider initiatives such as (i) securing enough education capacity in relevant fields at regional universities, (ii) facilitating mobility of highly educated individuals from other regions nationally and internationally, (iii) supporting ‘return migration’, which tends to strengthen inter-regional and international linkages and networks, and (iv) creating incentives to attract specialized knowledge-intensive service firms into the region as well as for potential entrepreneurs in the region to start such firms.

Finally, the regional innovation policy-mix must change over time as internal and external conditions change, which implies that there is no such thing as an optimal policy-mix from a static point of view. It is also essential to integrally relate the goals, design and implementation of regional innovation policies to broader decisions on the direction of the long-term and path-dependent development strategy at the regional level, which accentuates the importance of policy governance (Magro & Wilson, 2019) but also the policy evaluation (Karlsson & Tavassoli, 2019). This also raises questions concerning whether the current development path of the current cluster of highly complex innovators is sustainable in the long run or if there is a need to find related or totally new development paths given the trends in technological development and international competition (Boschma, 2017).

In summary, regional innovation policies should overall focus on increasing the agglomeration externalities, which, in turn, will increase for example intraregional knowledge spillover, i.e. with reference to the notion of “success breeds success”. Having said that, we want to emphasize that optimal regional innovation policy-mix will differ between regions according to the specific regional conditions in each region, since ‘one size doesn’t fit all’ (Tödtling & Trippl, 2005). Our discussion about policy implication concerns regions that host firms that are highly complex innovators. For regions that lack such innovators, the above policy suggestions do not guarantee the emergence of highly complex innovators in these regions. Instead, for such lowly complex innovators, the 'usual suspect' factors such as frm's internal resources and investments as well as formal collaboration with external partners have a significant role. Hence policy makers should aim to nurture such factors. This implies that regional policy makers needs to adopt their policy mix depending on the complexity of innovation outcome of firms in a given region (and not just the dichotomous innovative versus non-innovative contingency approach).

6.4. Limitation and future research

There are few limitations in this study that propose avenue for future research. First, our result shows that the importance of internal resources (such as investment in R&D) seems to fade way for very complex innovators, while agglomeration externalities seems to play more pivotal role for them. This is an initial indication of 'substitutability'. But more systematic investigation of substitutability versus complementarity between firm-level (both internal and external factors) and agglomeration economies variables (regional variables) is needed. This will provide a more holistic picture for determinants of innovation outcomes of firms, particularly complexity of the outcomes, at different level of analysis. Second, even though we made use of panel nature of the data and employed lagged structure for explanatory variables, we only can claim positive 'associations' between regional factors and the complexity of innovation outcomes of firms. This has been an important first step. Further endeavors in dealing with endogeneity issues can pave the way for identifying a possible causal relationship between our identified regional factors and the complexity of innovation outcomes. And third, even though we controlled for sectoral heterogeneity of firms in our sample, we did not explicitly account for the industry lifecycle effects (Tavassoli, 2015). A further investigation is needed in order to uncover to what extent the relationship between innovation complexity and the geographic factors studied here is a result of the firms' location choices based on their life cycle stage.

References

Abernathy, W.J. & J.M. Utterback (1978), Patterns of Industrial Innovation, *Technology Review 80*, 40-47

Acs, Z.J. (2000), *Innovation and the Growth of Cities*, Edward Elgar, Northampton, MA

Acs, Z. J., Braunerhjelm, P., Audretsch, D. B., & Carlsson, B. (2009). The knowledge spillover theory of entrepreneurship. *Small business economics*, 32(1), 15-30.

Antonelli, C. F. Crespi & G. Scellato (2013), Internal and External Factors in Innovation Persistence, *Economics of Innovation and New Technology 22*, 256-280

Arora, A. & A. Gambardella (1990), Complementarity and External Linkages: The Strategies of Large Firms in Biotechnology, *Journal of Industrial Economics 38*, 361-379

Barca, F. (2009), An Agenda for a Reformed Cohesion Policy: A Place-Based Approach to Meeting European Union Challenges and Expectations, European Commission, Brussels

Bartoloni, E., & Baussola, M. (2016). Does technological innovation undertaken alone have a real pivotal role? Product and marketing innovation in manufacturing firms. *Economics of Innovation and New Technology*, 25(2), 91-113.

Bathelt, H., Malmberg, A., & Maskell, P. (2004). Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation. *Progress in human geography*, 28(1), 31-56.

Bonanno, G.& B. Haworth (1998), Intensity of Competition and the Choice between Product and Process Innovation, *International Journal of Industrial Organization 16*, 495-510

Boschma, R. (2017), Relatedness as a Driver of Regional Diversification: A Research Agenda, Regional Studies 51, 351-364

Brouwer, E. & A. Kleinknecht (1999), Innovative Output, and a Firm's Propensity to Patent. An Exploration of CIS Micro Data, *Research Policy 28*, 615-624

Brown, R. (2016), Mission Impossible? Entrepreneurial Universities and Peripheral Regional Innovation Systems, Industry and Innovation 23, 189-205

Brunow, S. & V. Miersch (2015), Innovation Capacity, Workforce Diversity and Intra-Industrial Externalities: A Study of German Establishments, in Kourtit, K., et al. (Eds.), *The Rise of the City: Spatial Dynamics in the Urban Century*, Edward Elgar, Cheltenham, 188.222

Cabagnols, A. & C. Le Bas (2002), Differences in the Determinants of Product and Process Innovations: The French Case, in Kleinknecht, A. & P. Mohnen (Eds.), *Innovation and Firm Performance*, Palgrave, New York, 112-149

Camagni, R., & Capello, R. (2002). Milieux innovateurs and collective learning: from concepts to measurement. In *The emergence of the knowledge economy* (pp. 15-45). Springer, Berlin, Heidelberg.

Cassiman, B. & R. Veuglers (2002), R&D Cooperation and Spillovers: Some Empirical Evidence from Belgium, *American Economic Review 92*, 1169-1184

Cassiman, B. & R. Veuglers (2006), In Search of Complementarity in Innovation Strategy: Internal R&D and External Knowledge Acquisition, *Management Science 52*, 62-82

Castaldi, C., Frenken, K., & Los, B. (2015). Related variety, unrelated variety and technological breakthroughs: an analysis of US state-level patenting. *Regional studies*, 49(5), 767-781.

Chesbrough, H. (2003), *Open Innovation: The New Imperative for Creating and Profiting from Technology*, Harvard Business School Press, Cambridge, MA

Coenen, L., Asheim, B., Bugge, M. M., & Herstad, S. J. (2017). Advancing regional innovation systems: What does evolutionary economic geography bring to the policy table?. Environment and Planning C, 35(4), 600-620.

Cohen, W. M. (2010). Fifty years of empirical studies of innovative activity and performance. In Handbook of the Economics of Innovation (Vol. 1, pp. 129-213). North-Holland.

Coles, M. G., & Smith, E. (1996). Cross-section estimation of the matching function: evidence from England and Wales. *Economica*, 589-597.

Cooke, P., & Morgan, K. (1994). The regional innovation system in Baden–Wurttemberg. International journal of technology management, 9(3-4), 394-429.

Crépon, B., E. Duguet & J. Mairesse (1998), Research, Innovation and Productivity: An Econometric Analysis at the Firm Level, *Economics of Innovation and New Technology 7*, 115-158

Dahlander, L. & D.M. Gann (2010), How Open Is Innovation?, *Research Policy 39*, 699-709

Damanpour, F. and D. Aravind (2012). "Managerial Innovation: Conceptions, Processes, and Antecedents." *Management and Organization Review* 8(3): 423-454.

Dodgson, M., D. Gann & A. Salter (2008), *The Management of Technological Innovation: Strategy and Practice*, 2nd ed., Oxford University Press, Oxford

Doloreux, D. and, Parto S. (2005), Regional Innovation Systems: Current Discourse and Unresolved Issues, *Technology in Society 24*, 243-263

Doloreux, D. & I.P. Gomez (2017), A Review of (almost) 20 Years of Regional Innovation Systems Research, *European Planning Studies 25*, 371-387
Dosi, G. (1988), The Sources, Procedures and Microeconomic Effects of Innovation, *Journal of Economic Literature XXVI*, 1120-1171
Du, J., J.H. Love & S. Roper (2007), The Innovation Decision: An Economic Analysis, *Technovation 27*, 766-773
Duranton, G., & Puga, D. (2001). Nursery cities: Urban diversity, process innovation, and the life cycle of products. *American Economic Review*, 91(5), 1454-1477.
Ejermo, O. (2005). Technological diversity and Jacobs' externality hypothesis revisited. *Growth and Change*, 36(2), 167-195.
Ennen, E., and A. Richter. 2010. The whole is more than the sum of its parts or is it? A review of the empirical literature on complementarities in organizations. *Journal of Management*, 36(1), 207–33.
Evangelista, R., & Vezzani, A. (2010). The economic impact of technological and organizational innovations. A firm-level analysis. *Research Policy*, 39(10), 1253-1263.
Flanagan, K. & E. Uyarra (2016), Four Dangers in Innovation Policy Studies – And how to Avoid Them, Industry and Innovation 23, 177-188
Feldman, M. P. (1994). The geography of innovation (Vol. 2). Springer Science & Business Media.
Feldman, M. P., & Kogler, D. F. (2010). Stylized facts in the geography of innovation. In *Handbook of the Economics of Innovation* (Vol. 1, pp. 381-410). North-Holland.
Feldman, M. P., & Tavassoli, S. (2015). Something new: Where do new industries come from. *The Oxford Handbook of Local Competitiveness*, 125-140.
Foss, N. (2004), *Resources, Firms and Strategies*, Oxford University Press, Oxford
Freel, M.S. (2005), Patterns of Innovation and Skills in Small Firms, *Technovation 25*, 123-134
Fritsch, M. & E. Schindele (2011), The Contribution of New Businesses to Regional Employment – An Empirical Analysis, Economic Geography 87, 153-180
Funk, R. J. (2014). Making the most of where you are: Geography, networks, and innovation in organizations. *Academy of Management Journal*, 57(1), 193-222.
Griliches, Z. (1979), Issues in Assessing the Contribution of Research and Development to Productivity Growth, *Bell Journal of Economics 10*, 92-116
Harris, R.I.D. & M. Trainor (1995), Innovation and R&D in Northern Ireland Manufacturing: A Schumpeterian Approach, *Regional Studies 29*, 593-604
Helfat, C.E. (1994), Evolutionary Trajectories in Petroleum Firm R&D., *Management Science 40*, 1720-1747
Huang, F. and J. Rice (2012). "Openness in product and process innovation." *International Journal of Innovation Management* 16(4).
Henderson, R. M., & Clark, K. B. (1990). Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative science quarterly 35*, 9-30.
Hervas-Oliver, J. L., Sempere-Ripoll, F., Boronat-Moll, C., & Rojas, R. (2015). Technological innovation without R&D: unfolding the extra gains of management innovations on technological performance. *Technology Analysis & Strategic Management*, 27(1), 19-38.
Hirsch-Kreinsen, H., et al. (2005), Low and Medium Technology Industries in the Knowledge Economy: The Analytical Issues, in Hirsch-Kreinsen, H., D. Jacobson & S. Laestadius (Eds.), *Low-Tech Innovation in the Knowledge Economy*, Peter Lang, Frankfurt am Main, 11-30
Horn, P.M. (2005), The Changing Nature of Innovation, *Research Technology Management 48*, 28-33
Huggins, R. & P. Thompson (2017), Entrepreneurial Networks and Open Innovation: The Role of Strategic and Embedded Ties, Industry and Innovation 24, 403-435
Iansiti, M. (1997), From Technology Potential to Product Performance: An Empirical Analysis, *Research Policy 26*, 345-365
Iansiti, M. & R. Levien (2004), *The Keystone Advantage*, Harvard Business School Press, Cambridge, MA
Isaksen, A., Tödtling, F., & Trippl, M. (2018). Innovation policies for regional structural change: Combining actor-based and system-based strategies. In New Avenues for regional innovation systems-Theoretical Advances, empirical cases and policy Lessons (pp. 221-238). Springer, Cham.
Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly journal of Economics*, 108(3), 577-598.
Joshi, A.W. & S. Sharma (2004), Customer Knowledge Development: Antecedents and Impact on New Product Performance, *Journal of Marketing 68*, 47-59
Karlsson, C. & A. Manduchi (2001), Knowledge Spillovers in a Spatial Context – A Critical Review and Assessment, in Fischer, M.M & J. Fröhlich (Eds.), Knowledge, Complexity and Innovation Systems, Springer, Berlin, 101-123
Karlsson, C., B. Johansson & R.R. Stough (2005) (Eds.), *Industrial Clusters and Inter-Firm Networks*, Edward Elgar, Cheltenham

Karlsson, C. & S. Tavassoli (2016), Innovation Strategies of Firms: What Strategies and Why?, *Journal of Technology Transfer 41*, 1483-1506
Karlsson, C. & S. Tavassoli (2019), Policy Evaluation in Competitiveness: Towards More Results-Oriented Industrial Policies, in Karlsson, C., D. Silander & B. Pircher (Eds.), Smart, Sustainable and Inclusive Growth. Political Entrepreneurship for a Prosperous Europe, Edward Elgar, Cheltenham, 128-158
Kleinknecht, A., K. von Montfort & E. Brouwer (2002), The Non-Trivial Choice between Innovation Indicators, *Economics of Innovation and New Technology 11*, 109-121
Klepper, S. (1996), Entry, Exit, Growth and Innovation over the Product Life Cycle, *American Economic Review 86*, 562-583
Klette, T.J. & F. Johansen (1998), Accumulation of R&D Capital and Dynamic Firm Performance: A Not-so-Fixed Model, *Annales de Économie et de Statistique 49/50*, 389-419
Kok, R.A.W. & W.G. Biemans (2009), Creating a Market-Oriented Product Innovation Process: A Contingency Approach, *Technovation 29*, 517-526
Krugman, P. (1991 a), Increasing Returns and Economic Geography, *Journal of Political Economy 99*, 483-499
Krugman, P. (1991 b), History and Location: The Case of the Manufacturing Belt, *American Economic Review 81*, 80-83
Krugman, P. (1993), First Nature, Second Nature and Metropolitan Location, *Journal of Regional Science 33*, 129-144
Landry, C. (2008), *The Creative City: A Toolkit for Innovators*, 2nd edn, Earthscan, London
Laursen, K. & N.J. Foss (2003), New Human Resource Management Practices, Complementarities and the Impact on Innovation Performance, *Cambridge Journal of Economics 27*, 243-263
Laursen, K., & Salter, A. (2006). Open for innovation: the role of openness in explaining innovation performance among UK manufacturing firms. *Strategic Management Journal*, 27(2), 131-150.
Levin, R.C., et al. (1987), Appropriating the Returns from Industrial Research and Development, *Brookings Papers on Economic Activity* 3, 783-831
Lew, Y. K., Khan, Z., & Cozzio, S. (2018). Gravitating toward the quadruple helix: international connections for the enhancement of a regional innovation system in Northeast Italy. R&D Management, 48(1), 44-59.
Li, Y., Y. Liu & F. Ren (2007), Product Innovation and Process Innovation in SOEs: Evidence from the Chinese Transition, *Journal of Technology Transfer 32*, 63-85
Lichtenhaler, U. & E. Lichtenhaler (2009), A Capacity-Based Framework for Open Innovation: Complementing Absorptive Capacity, *Journal of Management Studies 46*, 1315-1338
Link, A.N., D. Paton & D.S. Siegel (2005), An Econometric Analysis of Trends in Research Joint Venture Activity, *Managerial and Decision Economics 26*, 149-158
Love, J.H. & S. Roper (2001), Location and Network Effects on Innovation Success: Evidence for UK, German and Irish Manufacturing Plants, *Research Policy 30*, 643-661
Love, J.H. & S. Roper (2009), Organizing the Innovation Process: Complementarities in Innovation Networks, *Industry and Innovation 16*, 273-290
Love, J. H., S. Roper, et al. (2011). "Openness, knowledge, innovation and growth in UK business services." *Research Policy* 40(10): 1438-1452.
Lööf, H., & Heshmati, A. (2006). On the relationship between innovation and performance: A sensitivity analysis. *Economics of Innovation and New Technology*, 15(4-5), 317-344.
Magro, E. & J.R. Wilson (2019), Policy-Mix Evaluation: Governance Challenges from New Place-Based Innovation Policies, Research Policy 48, 1-10
Marques, P. & K. Morgan (2018), The Heroic Assumptions of Smart Specialization: A Sympathetic Critique of Regional Innovation Policy, in Isaksen, A., R. Martin & M. Trippl (Eds.), New Avenues for Regional Innovation Systems – Theoretical Advances, Empirical Cases and Policy Lessons, Springer, New York, 275-293
Martin, R. & M. Trippl (2014), System Failures, Knowledge Bases and Regional Innovation Policies, disP – The Planning Review 50, 24-32
McCann, B. T., & Folta, T. B. (2008). Location matters: where we have been and where we might go in agglomeration research. Journal of management, 34(3), 532-565.
McGuirk, H. & D. Jordan (2012), Local Labor Market Diversity and Business Innovation: Evidence from Irish Manufacturing Businesses, *European Planning Studies 20*, 1945-1960
Medrano, N., & Olarte-Pascual, C. (2016). The effects of the crisis on marketing innovation: an application for Spain. *Journal of Business & Industrial Marketing*, 31(3), 404-417.
Mohnen, P. (1991), Survol de la Littérature sur les Externalités Technologiques, in De Bandt, F. & D. Foray (Eds.), *L'évoluation Economique de la Recherche et du Changement Technologique*, Editions de CNRS, Paris
Nauwelaers, C. & R. Wintjes (2003), Towards a New Paradigm for Innovation Policy?, in Asheim, B., et al. (Eds), Regional Innovation Policy for Small – Medium Sized Enterprises, Edward Elgar, Cheltenham, 193-219
Nijkamp, P. (2003), Entrepreneurship in a Modern Network Economy, *Regional Studies 37*, 395-405

OECD (2005), *Oslo Manual: Proposed Guidelines for Collecting and Interpreting Technological Innovations*, OECD, Paris

Penrose, E.T. (1959), *The Theory of the Growth of the Firm*, John Wiley & Sons, New York, NY

Pinto, H., & Fernández-Esquinas, M. (2018). What do stakeholders think about knowledge transfer offices? The perspective of firms and research groups in a regional innovation system. Industry and Innovation, 25(1), 25-52.

Porter, M. E., & Stern, S. (2001). Location matters. *Sloan Management Review*, 42(4), 28-36.

Ronde, P., & Hussler, C. (2005). Innovation in regions: What does really matter?. *Research Policy,* 34(8), 1150-1172.

Roper, S., J. Du & J. Love (2008), Modelling the Innovation Value Chain, *Research Policy 37*, 961-977

Roper, S., N. Hewitt-Dundas & J.H. Love (2004), An Ex Ante Evaluation Framework for the Regional Benefits of Publicly Supported R&D Projects, *Research Policy 33*, 487-509

Schmidt T. & C. Rammer (2007), Non-Technological and Technological Innovation: Strange Bedfellows? *Working Paper 07-052*, ZEW, Mannheim

Schubert, T. (2010). Marketing and organisational innovations in entrepreneurial innovation processes and their relation to market structure and firm characteristics. *Review of Industrial Organization*, 36(2), 189-212.

Schumpeter, J. (1934), *The Theory of Economic Development*, Harvard University Press, Cambridge, Massachusetts.

Shapero, A. (1984), The Entrepreneurial Event, in Kent, C.A. (Ed.), *The Environment for Entrepreneurship*, Lexington Books, Lexington, MA, 21-40

Strambach, S. & B. Klement (2012), Cumulative and Combinatorial Micro-Dynamics of Knowledge. The Role of Space and Place in Knowledge Integration, European Planning Studies 20, 1843-1866

Stuart, T.E. & J.M. Podolny (1996), Local Search and the Evolution of Technological Capabilities, *Strategic Management Journal 17*, 21-38

Takeishi, A. (2001), Bridging Inter- and Intra-Firm Boundaries: Management of Supplier Involvement in Automobile Product Development, *Strategic Management Review 22*, 403-433

Tavassoli, S., & Carbonara, N. (2014). The role of knowledge variety and intensity for regional innovation. *Small Business Economics*, 43(2), 493-509.

Tavassoli, S. (2015). Innovation determinants over industry life cycle. *Technological Forecasting and Social Change*, 91, 18-32.

Tavassoli, S. & C. Karlsson (2017), The Role of the Regional Context on Innovation Persistency of Firms, *Papers in Regional Science 97*, 931-956

Tavassoli, S., & Bengtsson, L. (2018). The role of business model innovation for product innovation performance. *International Journal of Innovation Management*, 22(07), 1850061.

Teece, D.J. (1986), Profiting from Technological Innovation: Implications for Integration, Collaboration, Licensing and Public Policy, *Research Policy 15*, 285-305

Teece, D.J., G. Pisano & A. Shuen (1997), Dynamic Capabilities and Strategic Management, *Strategic Management Journal 18*, 509-533

Teece, D.J. (2017). Business models and dynamic capabilities. Long Range Planning, 51(1), 40–49.

Tödtling, F. & M. Trippl (2005), One Size Fits All? Towards a Differentiated Regional Innovation Policy Approach, Research Policy 34, 1203-1219

Utterback, J.M. & W.J. Abernathy (1975), A Dynamic Model of Process and Product Innovation, *OMEGA. The International Journal of Management Science* 6, 639-656

Vernon, R. (1966), International Investments and International Trade in the Product Cycle, *Quarterly Journal of Economics 80*, 190-207

Versapgen, B. & T.H. Clausen (2012), The Dynamics of Innovation Strategies, in Andersson, M., et al. (Eds.), *Innovation and Growth. From R&D Strategies of Innovating Firms to Economy-Wide Technological Change*, Oxford University Press, Oxford, 38-56

Veuglers, R. & B. Cassiman (1999), Make and Buy Innovation Strategies: Evidence from Belgian Manufacturing Firms, *Research Policy 28*, 63-80

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

Table 1-Descriptive Statistics of variables

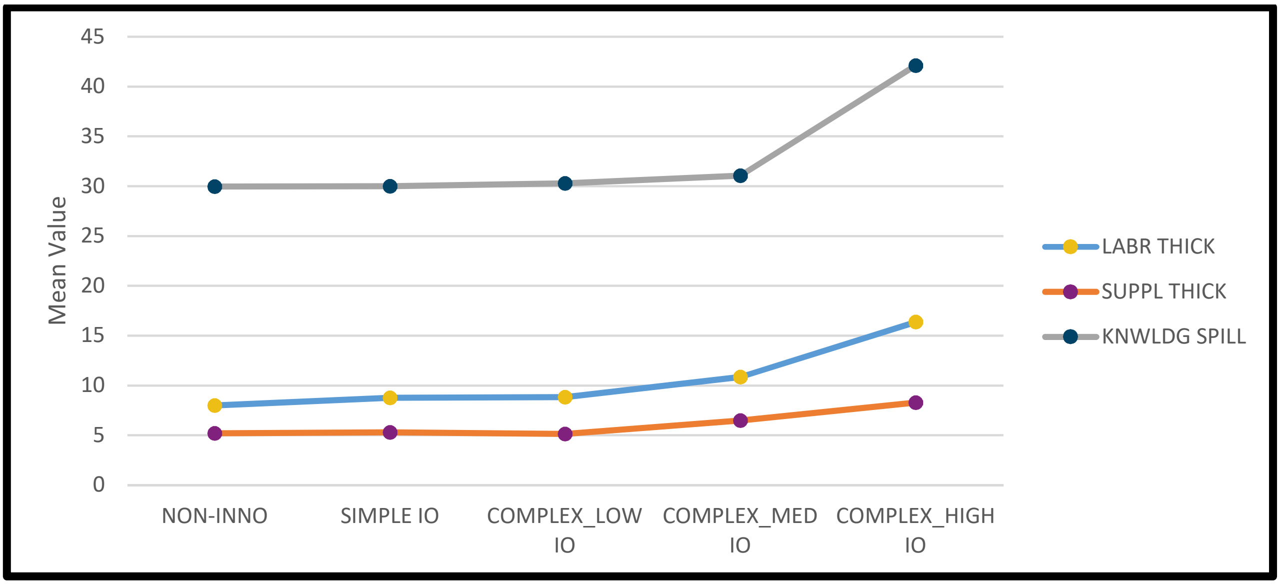
Variables	Observations	Mean	Std. Dev.	Min	Max
$LABR\ THICK_{ir}$	1722	8.89	2.00	2.30	11.39
$SUPPL\ THICK_{ir}$	1722	5.40	3.61	0	9.42
$KNWLDG\ SPILL_{ir}$	1722	32.40	32.19	0	88
$RDIN_{it}$	1722	0.47	0.50	0	1
$RDEX_{it}$	1722	0.31	0.46	0	1
$CONT.R\&D_{it}$	1722	0.30	0.46	0	1
$MACH_{it}$	1722	0.48	0.50	0	1
$EXKN_{it}$	1722	0.32	0.47	0	1
$TRAINING_{it}$	1722	0.31	0.46	0	1
$MARK_{it}$	1722	0.28	0.45	0	1
COS_{it}	1722	0.29	0.46	0	1
$COCL_{it}$	1722	0.15	0.35	0	1
$COCOM_{it}$	1722	0.12	0.32	0	1
$COUNIV_{it}$	1722	0.33	0.76	0	5
$COINST_{it}$	1722	0.15	0.52	0	5
$SIZE_{it}$	1722	4.51	1.52	2.30	9.88
$PHYSICAL\ CAP_{it}$	1722	16.59	3.28	0	23.86
$HUMAN\ CAP_{it}$	1722	0.16	0.18	0	0.89
$IMPORT_{it}$	1722	0.13	0.17	0	1
$EXPORT_{it}$	1722	0.25	0.33	0	1
$UNINATIONAL_{i}$	1722	0.32	0.47	0	1
$DOMESTIC\ MNE_{i}$	1722	0.26	0.44	0	1
$FOREIGN\ MNE_{i}$	1722	0.29	0.45	0	1
$MANUF_{i}$	1722	0.66	0.47	0	1

Table 2-Innovation Outcomes (IO): various combination of Schumpeterian innovation types

#	**Innovation Outcome (IO)**	Frequency	Percentage (Total)	Percentage (Innovative)
1	NON-INNO	600	35%	-
2	SIMPLE IO	380	22%	34%
3	COMPLEX_LOW IO	337	19%	30%
4	COMPLEX_MED IO	242	14%	21%
5	COMPLEX_HIGH IO	163	10%	15%
	Total	1722	100%	100%

Notes for Table 2: The table shows the 5 possible innovation outcome categories that firms manage to introduce, considering various types of Schumpeterian innovation. For the purpose of this study, we use four (out of five) types of Schumpeterian innovation, which are: product, process, marketing, and organizational innovation. According to OECD (2005), a *product innovation* is the market introduction of a new or significantly improved good or service with respect to its capabilities, user friendliness, components or sub-systems. Product innovations (new or improved) must be new to the enterprise, but they do not need to be new to the market. A *process innovation* is the implementation of a new or significantly improved production process, distribution method, or support activity for goods or services, such as maintenance systems or operations for purchasing, accounting, or computing (exclude purely organizational innovation). Process innovations must be new to the enterprise, but they do not need to be new to your market. A *marketing innovation* is the implementation of a new marketing concept or strategy that differs significantly from the enterprise's existing marketing methods and which has not been used before. It requires significant changes in product design or packaging, product placement, product promotion or pricing. It excludes seasonal, regular and other routine changes in marketing methods. An *organizational innovation* is a new organizational method in the enterprise's business practices (including knowledge management), workplace organization and decision making, or external relations that has not been previously used by the enterprise. It must be the result of strategic decisions taken by management. It excludes mergers or acquisitions, even if for the first time.

Figure 1-Various Innovation Outcomes (IO) across regional characteristics



Notes for Figure 1: The Figure shows how the mean value of the three regional characteristic (Y-axis) varies for various innovation outcomes of firm. It basically illustrates '*where'* each of the five types of innovation outcomes occur in terms of three regional characteristics.

Table 3-Effect of Labor Market Thickness on Innovation Outcomes (IO) of firms

VARIABLES	(1) Simple IO	(2) Complex_Low IO	(3) Complex_Medium IO	(4) Complex_High IO
$LABR\ THICK_{ir-1}$	0.941	1.020	1.015	1.148**
	(0.035)	(0.043)	(0.046)	(0.078)
$RDIN_{it-1}$	1.260**	1.435**	1.408*	1.366
	(0.280)	(0.327)	(0.358)	(0.516)
$RDEX_{it-1}$	1.562*	0.976	1.430	0.728
	(0.358)	(0.229)	(0.355)	(0.203)
$CONT\ RD_{it-1}$	1.186	1.317	1.090	1.656
	(0.325)	(0.347)	(0.315)	(0.541)
$MACH_{it-1}$	1.268	1.536**	2.263***	1.549
	(0.248)	(0.297)	(0.508)	(0.443)
$EXKN_{it-1}$	0.906	1.267	1.195	1.451
	(0.192)	(0.281)	(0.272)	(0.399)
$TRAINING_{it-1}$	1.293	1.120	1.037	1.297
	(0.261)	(0.224)	(0.235)	(0.343)
$MARK_{it-1}$	1.026	1.085	1.451	2.053**
	(0.228)	(0.257)	(0.348)	(0.580)
$COSUP_{it-1}$	1.469	1.358	1.576*	1.971**
	(0.366)	(0.362)	(0.428)	(0.633)
$COCUS_{it-1}$	1.026	1.186	1.321	1.222
	(0.321)	(0.377)	(0.424)	(0.433)
$COCOM_{it-1}$	1.187	1.279	0.714	0.712
	(0.394)	(0.425)	(0.246)	(0.262)
$COUNI_{it-1}$	0.820	0.953	1.060	1.261
	(0.205)	(0.233)	(0.244)	(0.319)
$COINS_{it-1}$	0.872	0.781	0.789	0.664
	(0.188)	(0.204)	(0.193)	(0.175)
$SIZE_{it-1}$	1.137*	1.345***	1.584***	1.880***
	(0.084)	(0.110)	(0.136)	(0.223)
$PHYCAP_{it-1}$	1.005	1.025	1.045	1.035
	(0.027)	(0.031)	(0.034)	(0.048)
$HUMCAP_{it-1}$	2.879**	1.621	3.908**	8.968**
	(1.537)	(0.873)	(2.540)	(7.791)
$IMPORT_{it-1}$	1.186	1.802	0.639	1.523
	(0.572)	(0.737)	(0.367)	(0.907)
$EXPORT_{it-1}$	1.036	1.660*	1.788**	2.012**
	(0.293)	(0.462)	(0.621)	(0.773)
$UNINAT_i$	1.009	1.040	1.159	0.758
	(0.239)	(0.233)	(0.408)	(0.351)
$DOM\ MNE_i$	0.805	0.653	1.011	0.606
	(0.220)	(0.186)	(0.371)	(0.299)
$FOR\ MNE_i$	0.940	0.621	0.651	0.429*
	(0.263)	(0.181)	(0.251)	(0.211)
$MANUF_i$	1.402*	1.420*	2.325***	4.206***
	(0.265)	(0.272)	(0.589)	(1.550)
Nr of Firms	574	574	574	574
Observations	1,722	1,722	1,722	1,722

Notes for Table 3: The table reports estimated Relative Risk Ration (RRR) with clustered standard errors in parentheses. ***, ** and * indicate significance on a 1%, 5% and 10% level. Multinomial Logit model is used for estimating the five innovation Outcome (IO) categories of all firms with being non-innovative as the base model (outcome). An RRR > 1 indicates a positive effect of the respective variable on a given innovation outcome category $j\neq0$ in compare with the reference innovation outcome category of being non-innovative (j=0). RRR < 1 has opposite meaning. Observations are pooled over t=2008, 2010, 2012. All time-variant explanatory variables are lagged one period in time (2 years). Both Hausman tests and suest-based Hausman tests of IIA assumption point that IIA assumption is not violated in the estimation. Time dummies are included in the regression model. The estimation is based on balanced panel data with 1722 observations. Unbalanced panel data reveals similar results.

Table 4-Role of Specialized Supplier Thickness Innovation Outcomes (IO) of firms

VARIABLES	(1') Simple IO	(2') Complex_Low IO	(3') Complex_Medium IO	(4') Complex_High IO
$SUPPL\ THICK_{rt-1}$	1.000	1.000	1.001	1.002***
	(0.001)	(0.001)	(0.001)	(0.001)
$RDIN_{it-1}$	1.261**	1.508**	1.424*	1.406
	(0.279)	(0.340)	(0.363)	(0.525)
$RDEX_{it-1}$	1.609**	0.999	1.439	0.729
	(0.365)	(0.234)	(0.358)	(0.202)
$CONT\ RD_{it-1}$	1.190	1.312	1.062	1.638
	(0.326)	(0.344)	(0.307)	(0.537)
$MACH_{it-1}$	1.303	1.521**	2.225***	1.522
	(0.253)	(0.292)	(0.500)	(0.431)
$EXKN_{it-1}$	0.885	1.292	1.225	1.496
	(0.185)	(0.284)	(0.279)	(0.407)
$TRAINING_{it-1}$	1.341	1.091	1.035	1.304
	(0.269)	(0.218)	(0.236)	(0.344)
$MARK_{it-1}$	1.013	1.079	1.454	2.000**
	(0.222)	(0.253)	(0.350)	(0.561)
$COSUP_{it-1}$	1.434	1.297	1.628*	2.051**
	(0.354)	(0.346)	(0.438)	(0.654)
$COCUS_{it-1}$	1.040	1.206	1.292	1.218
	(0.325)	(0.382)	(0.415)	(0.434)
$COCOM_{it-1}$	1.194	1.273	0.708	0.702
	(0.397)	(0.423)	(0.245)	(0.260)
$COUNI_{it-1}$	0.837	0.977	1.053	1.251
	(0.208)	(0.239)	(0.243)	(0.312)
$COINS_{it-1}$	0.859	0.774	0.790	0.653
	(0.184)	(0.199)	(0.193)	(0.173)
$SIZE_{it-1}$	1.139*	1.351***	1.608***	1.904***
	(0.085)	(0.111)	(0.139)	(0.229)
$PHYCAP_{it-1}$	1.004	1.027	1.043	1.033
	(0.027)	(0.031)	(0.034)	(0.047)
$HUMCAP_{it-1}$	2.527*	1.484	4.385**	9.539***
	(1.334)	(0.791)	(2.792)	(8.236)
$IMPORT_{it-1}$	1.298	1.784	0.668	1.739
	(0.625)	(0.732)	(0.388)	(1.012)
$EXPORT_{it-1}$	1.092	1.758**	1.796*	2.085*
	(0.310)	(0.489)	(0.631)	(0.794)
$UNINAT_i$	0.969	0.935	1.157	0.732
	(0.227)	(0.206)	(0.409)	(0.337)
$DOM\ MNE_i$	0.763	0.575*	0.989	0.546
	(0.208)	(0.164)	(0.366)	(0.270)
$FOR\ MNE_i$	0.879	0.544**	0.625	0.383*
	(0.247)	(0.159)	(0.243)	(0.188)
$MANUF_i$	1.416*	1.488**	2.361***	4.692***
	(0.267)	(0.283)	(0.609)	(1.725)
Nr of Firms	574	574	574	574
Observations	1,722	1,722	1,722	1,722

Notes for Table 4: The table reports estimated Relative Risk Ration (RRR) with clustered standard errors in parentheses. ***, ** and * indicate significance on a 1%, 5% and 10% level. Multinomial Logit model is used for estimating the five innovation Outcome (IO) categories of all firms with being non-innovative as the base model (outcome). An RRR > 1 indicates a positive effect of the respective variable on a given innovation outcome category $j \neq 0$ in compare with the reference innovation outcome category of being non-innovative ($j=0$). RRR < 1 has opposite meaning. Observations are pooled over t=2008, 2010, 2012. All time-variant explanatory variables are lagged one period in time (2 years). Both Hausman tests and suest-based Hausman tests of IIA assumption point that IIA assumption is not violated in the estimation. Time dummies are included in the regression model. The estimation is based on balanced panel data with 1722 observations. Unbalanced panel data reveals similar results.

Table 5-Role of knowledge spillover Innovation Outcomes (IO) of firms

VARIABLES	(1'') Simple IO	(2'') Complex_Low IO	(3'') Complex_Medium IO	(4'') Complex_High IO
$KNWLDG\ SPILL_{rt-1}$	0.999	1.003	1.001	1.012***
	(0.003)	(0.003)	(0.003)	(0.004)
$RDIN_{it-1}$	1.260**	1.508**	1.426*	1.413
	(0.279)	(0.341)	(0.363)	(0.528)
$RDEX_{it-1}$	1.609**	1.000	1.439	0.731
	(0.366)	(0.234)	(0.358)	(0.203)
$CONT\ RD_{it-1}$	1.190	1.312	1.064	1.627
	(0.326)	(0.344)	(0.308)	(0.533)
$MACH_{it-1}$	1.302	1.520**	2.225***	1.528
	(0.253)	(0.292)	(0.500)	(0.433)
$EXKN_{it-1}$	0.886	1.292	1.226	1.485
	(0.185)	(0.284)	(0.279)	(0.404)
$TRAINING_{it-1}$	1.340	1.092	1.036	1.313
	(0.269)	(0.218)	(0.236)	(0.346)
$MARK_{it-1}$	1.013	1.079	1.451	2.000**
	(0.222)	(0.253)	(0.349)	(0.562)
$COSUP_{it-1}$	1.434	1.296	1.627*	2.055**
	(0.354)	(0.345)	(0.438)	(0.655)
$COCUS_{it-1}$	1.042	1.204	1.296	1.218
	(0.326)	(0.381)	(0.416)	(0.433)
$COCOM_{it-1}$	1.194	1.275	0.709	0.701
	(0.397)	(0.424)	(0.245)	(0.260)
$COUNI_{it-1}$	0.836	0.976	1.050	1.244
	(0.208)	(0.239)	(0.242)	(0.311)
$COINS_{it-1}$	0.858	0.775	0.791	0.656
	(0.184)	(0.200)	(0.193)	(0.174)
$SIZE_{it-1}$	1.139*	1.350***	1.606***	1.899***
	(0.085)	(0.111)	(0.139)	(0.230)
$PHYCAP_{it-1}$	1.005	1.027	1.044	1.035
	(0.027)	(0.031)	(0.034)	(0.047)
$HUMCAP_{it-1}$	2.525*	1.478	4.284**	9.005**
	(1.335)	(0.789)	(2.739)	(7.814)
$IMPORT_{it-1}$	1.300	1.775	0.664	1.689
	(0.626)	(0.728)	(0.384)	(0.988)
$EXPORT_{it-1}$	1.094	1.763**	1.812*	2.117**
	(0.311)	(0.492)	(0.636)	(0.809)
$UNINAT_i$	0.968	0.933	1.151	0.724
	(0.227)	(0.205)	(0.406)	(0.333)
$DOM\ MNE_i$	0.761	0.574*	0.980	0.543
	(0.208)	(0.164)	(0.362)	(0.268)
$FOR\ MNE_i$	0.877	0.543**	0.619	0.378**
	(0.246)	(0.159)	(0.241)	(0.185)
$MANUF_i$	1.420*	1.486**	2.383***	4.707***
	(0.267)	(0.283)	(0.612)	(1.729)
Nr of Firms	574	574	574	574
Observations	1,722	1,722	1,722	1,722

Notes for Table 5: The table reports estimated Relative Risk Ration (RRR) with clustered standard errors in parentheses. ***, ** and * indicate significance on a 1%, 5% and 10% level. Multinomial Logit model is used for estimating the five innovation Outcome (IO) categories of all firms with being non-innovative as the base model (outcome). An RRR > 1 indicates a positive effect of the respective variable on a given innovation outcome category $j \neq 0$ in compare with the reference innovation outcome category of being non-innovative (j=0). RRR < 1 has opposite meaning. Observations are pooled over t=2008, 2010, 2012. All time-variant explanatory variables are lagged one period in time (2 years). Both Hausman tests and suest-based Hausman tests of IIA assumption point that IIA assumption is not violated in the estimation. Time dummies are included in the regression model. The estimation is based on balanced panel data with 1722 observations. Unbalanced panel data reveals similar results.

Appendix 1-Variable definitions

Variables	Type*	Definitions
$SIMPLE\ IO_{rt}$	DV	1 if firm *i* in year *t* successfully introduces 1 type of innovation outcome (e.g. product innovation), 0 otherwise
$COMPLEX\_LOW\ IO_{rt}$	DV	1 if firm *i* in year *t* successfully introduces 2 types of innovation outcomes simultaneously (e.g. product and process innovation), 0 otherwise
$COMPLEX\_MED\ IO_{rt}$	DV	1 if firm *i* in year *t* successfully introduces 3 types of innovation simultaneously (e.g. product, process, and marketing innovation), 0 otherwise
$COMPLEX\_HIGH\ IO_{rt}$	DV	1 if firm *i* in year successfully introduces *all* 4 types of innovation (i.e. product, process, marketing, and organizational innovation), 0 otherwise
$LABR\ THICK_{rt}$	EV	Labor Market Thickness: The total number of employees with at least three years of university education in functional region r in year t minus firm *i*'s employment (log).
$SUPPL\ THICK_{rt}$	EV	Specialized Supplier Thickness: The number of employees in KIS** sector in functional region r in year t minus firm i's employment located in region r, if firm *i* is in KIS sector itself (log).
$KNWLDG\ SPILL_{rt}$	EV	Knowledge Spillover: The number of innovative firms in functional region r in year t minus firm *i* located in region r, if firm *i* is innovative itself (log). An innovative firm is identified if it introduces any of the four Schumpeterian innovation outputs (product process, organizational, and marketing innovation) in year t.
$RDIN_{it}$	C	1 if firm *i* had engagement in intramural R&D investment in year *t*, 0 otherwise
$RDEX_{it}$	C	1 if firm *i* had engagement in extramural R&D investment in year *t*, 0 otherwise
$CONT.R\&D_{it}$	C	1 if firm *i* in year *t* had continuous R&D investments over the past two years, 0 otherwise
$MACH_{it}$	C	1 if firm *i* had engagement in acquisition of machinery in year *t*, 0 otherwise
$EXKN_{it}$	C	1 if firm *i* had engagement in acquisition of external knowledge in year *t*, 0 otherwise
$TRAINING_{it}$	C	1 if firm *i* had engagement in training of employees for innovative activities in year *t*, 0 otherwise
$MARK_{it}$	C	1 if firm *i* had engagement i market introduction of innovation in year *t*, 0 otherwise
COS_{it}	C	1 if firm *i* had cooperation arrangements on innovation activities with suppliers in year *t*, 0 otherwise
$COCL_{it}$	C	1 if firm *i* had cooperation arrangements on innovation activities with clients in year *t*, 0 otherwise
$COCOM_{it}$	C	1 if firm *i* had cooperation arrangements on innovation activities with competitors in year *t*, 0 otherwise
$COUNIV_{it}$	C	1 if firm *i* had cooperation arrangements on innovation activities with universities in year *t*, 0 otherwise
$COINST_{it}$	C	1 if firm *i* had cooperation arrangements on innovation activities with public and/or private research institutes in year *t*, 0 otherwise
$SIZE_{it}$	C	Number of employees in firm *i* year *t* (log)
$PHYSICAL\ CAP_{it}$	C	Sum of investments in Buildings and Machines at year's end for firm *i* in year *t* (log)
$HUMAN\ CAP_{it}$	C	Share of employees with 3 or more years of university educations in firm *i* in year *t*
$IMPORT_{it}$	C	The amount (value in SEK) of import per employee for firm *i* in year *t* (log)
$EXPORT_{it}$	C	The amount (value in SEK) of export per employee for firm *i* in year *t* (log)
$UNINATIONAL_{i}$	C	1 if firm *i* belongs to a group and is uninational, 0 otherwise (Non-affiliated as base)
$DOMESTIC\ MNE_{i}$	C	1 if firm *i* belongs to group and is a domestic multinational enterprise, 0 otherwise
$FOREIGN\ MNE_{i}$	C	1 if firm belongs to group and is a foreign multinational enterprise, 0 otherwise
$MANUF_{i}$	C	1 if firm belongs to manufacturing sector, 0 otherwise captured by forty two industry sector dummies
Time Dummies	C	Time-specific component captured by three time dummies

* DV corresponds to Dependent Variable, EV corresponds to Explanatory Variable, and C corresponds to Control variable.
**KIS: Knowledge Intensive Services, which corresponds to the following NACE codes: 61-62 (Water transport; air transport), 64 (Post and telecommunication), 65-67 (Financial intermediation), 70 (Real estate activities), 71 (Renting of machinery and equipment), 72 (Computer and related activities), 73 (Research and development), 74 (Other business activities), 80 (Education), 85 (Health and social work), 92 (Recreational, cultural and sporting activities.

Appendix 2-Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(1)$LABR\ THICK$	1																							
(2)$SUPPL\ THICK$	0,87	1																						
(3)$KNWLDG\ SPILL$	0,88	0,83	1																					
(4)$RDIN$	0,02	0,03	0,01	1																				
(5)$RDEX$	0,01	0,01	0,01	0,59	1																			
(6)$CONT.R\&D$	0,04	0,06	0,03	0,7	0,55	1																		
(7)$MACH$	-0,02	-0,02	-0,01	0,55	0,44	0,42	1																	
(8)$EXKN$	0,01	0,02	0,03	0,44	0,47	0,38	0,53	1																
(9)$TRAINING$	0,01	0,01	0,01	0,5	0,42	0,46	0,54	0,42	1															
(10)$MARK$	0,05	0,04	0,04	0,53	0,48	0,53	0,45	0,42	0,48	1														
(11)COS	0,01	0,01	0	0,53	0,54	0,49	0,48	0,45	0,4	0,44	1													
(12)$COCL$	-0,01	0	-0,03	0,4	0,39	0,42	0,31	0,27	0,38	0,36	0,54	1												
(13)$COCOM$	0,03	0,04	0,04	0,3	0,35	0,3	0,26	0,25	0,24	0,23	0,46	0,35	1											
(14)$COUNIV$	0,1	0,1	0,1	0,41	0,5	0,47	0,35	0,35	0,36	0,37	0,54	0,45	0,48	1										
(15)$COINST$	0,05	0,05	0,07	0,29	0,37	0,35	0,25	0,27	0,28	0,28	0,39	0,32	0,4	0,7	1									
(16)$SIZE$	0,1	0,11	0,12	0,3	0,33	0,34	0,28	0,23	0,27	0,3	0,31	0,19	0,25	0,36	0,29	1								
(17)$PHYSIC\ CAP$	-0,11	-0,11	-0,11	0,16	0,25	0,22	0,2	0,14	0,15	0,16	0,22	0,11	0,19	0,23	0,18	0,56	1							
(18)$HUMAN\ CAP$	0,32	0,34	0,32	0,18	0,17	0,25	0,09	0,12	0,14	0,15	0,15	0,15	0,18	0,33	0,26	0,07	-0,12	1						
(19)$IMPORT$	0,02	0,04	-0,01	0,18	0,15	0,19	0,12	0,07	0,09	0,15	0,11	0,09	0,02	0,08	0,04	0,15	0,11	-0,04	1					
(20)$EXPORT$	-0,08	-0,07	-0,11	0,38	0,34	0,41	0,24	0,19	0,2	0,3	0,25	0,2	0,1	0,23	0,14	0,22	0,18	0,02	0,43	1				
(21)$UNINAT$	-0,02	-0,05	-0,01	-0,22	-0,22	-0,24	-0,13	-0,14	-0,17	-0,17	-0,15	-0,13	-0,06	-0,13	-0,09	-0,36	-0,09	-0,03	-0,29	-0,34	1			
(22)$DOM\ MNE$	0	0,04	0	0,21	0,21	0,22	0,14	0,16	0,14	0,16	0,18	0,14	0,11	0,12	0,05	0,21	0,08	0,06	0,14	0,22	-0,4	1		
(23)$FOR\ MNE$	0,11	0,11	0,11	0,13	0,15	0,16	0,11	0,08	0,11	0,14	0,08	0,05	0,02	0,12	0,12	0,4	0,17	0,05	0,25	0,26	-0,43	-0,38	1	
(24)$MANUF$	-0,24	-0,23	-0,27	0,24	0,16	0,2	0,18	0,11	0,1	0,16	0,13	0,12	0	0,06	0,03	-0,02	0,03	-0,35	0,28	0,44	-0,22	0,17	0,05	1