Innovation, Agglomeration, and Knowledge Spillovers: An Empirical Study of Finnish and Swedish Firms

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Abstract

This paper modifies the traditional knowledge production function by considering regional human capital, firms' membership in industrial agglomerations, and measures of knowledge spillovers as potential sources of agglomeration economies in explaining firms' patent production. Since distributions of patent counts are over-dispersed with excess zeros, this study applies the Zero-inflated Negative Binominal model to analyze a panel of 147 Finnish and Swedish firms during 2002-2005. This paper finds that firm size, intensity of cumulated research and development investment and regional human capital are the main attributes in increasing firm innovation output. However, industrial agglomerations may not be consistently effective across all the industries and regions examined in strengthening firms' patent production. In addition, cross-region knowledge spillovers positively affect patenting intensity, while the effect of within-region knowledge spillovers varies by industries studied in this paper.

JEL classification: L25, O32, R12, R30

Keywords: Industrial agglomeration; patent count; innovation; knowledge spillovers; Zero-inflated Negative Binomial model

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1. Introduction

It has been increasingly and widely reconciled across the Member States in the European Union (EU) in policy agendas like the Lisbon Strategy (2000), the Barcelona strategy (2002) and the renewed Lisbon Strategy (2005)[1] that research and development (R&D) investment is essential in encouraging long-run growth and job creation (COM, 2003). Regardless of immense policy interest, the EU R&D intensity, defined as percentage of Gross Domestic Product (GDP), amounted to 1.84%, which is lower than in the U.S. and Japan. However, according to newly announced 2007 figures, the Nordic countries, Sweden and Finland, spend notably more than the Barcelona 3% of GDP on R&D (European Commission, 2007). Evaluating their figures of innovation inputs and patent production, the two Nordic countries appear to be far more efficient than the U.S. in the innovation process at the macro- and the micro-economic level (Baudry and Dumont, 2006). Furthermore, the geographic concentration of innovation can be underlined by the fact that among the ten most innovative European regions, half of them are located in Sweden and Finland.[2]

To identify the determinants of technological advancement in the form of patenting, it is straightforward to apply the most predominant model founded in the literature on innovation and technological change, the "Griliches" model of knowledge production function (KPF) (Griliches, 1979; Pakes and Griliches, 1980). The model of the KPF associating R&D, the key knowledge generating input, with innovative output robustly holds at aggregate levels of the country and industry (Scherer, 1982, Griliches, 1984). However, it becomes less convincing at the disaggregated level of the firm due to the weak empirical relationship found between R&D inputs and innovative output (Acs and Audretsch, 1990). The literature of localized knowledge spillovers raises an important stylized fact that benefits from knowledge spillovers encourage sectors to agglomerate. Equipping with novel understandings on knowledge spillovers and agglomeration, recent studies draw attention to the presence of externalities as an alternative cause of technological advancement at either a spatial unit of observation or an industrial level (Jaffe, 1989;

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[1] At the Barcelona Summit in March, 2002, European Council committed to increase the R&D investment to 3% of GDP and the share of R&D expenditure funded by private sector to two-thirds by 2010. See various annual March issues of Presidency Conclusions, http://www.consilium.europa.eu/App/newsroom/loadbook.aspx?BID=76&LANG=1&cmsid=347.

2 There are 208 regions and seven indicators listed in 2006 Regional Innovation Scoreboard (RIS). For sources and definitions of indicators available at: www.trendchart.org/scoreboards/scoreboard2006/pdf/eis_2006_global_innovation_report.pdf.

Audretsch and Feldman, 1996; Anselin et al., 1997; Branstetter, 2001; Adams, 2002; Ketelhöhn, 2006; OhUallachain and Leslie, 2007). Refocusing on the KPF at the firm level, this study modifies the conventional model by incorporating potential sources of externalities, such as knowledge spillovers and industrial agglomeration, for explaining innovation.

The interactions between innovative activities and industrial agglomeration, especially about the role of knowledge spillovers in advocating innovation, have attracted growing attentions in recent years. But only lately have there been limited empirical studies using firm level data to examine relationships between innovation and spatial agglomeration (among others, Baptista and Swann, 1998; Beaudry and Breschi, 2000; Cainelli and De Liso, 2005). In particular, Johansson and Lööf (2008) provide an empirical study on the innovative performance of Swedish firms and emphasize the role of location versus firm characteristics. Existing studies hitherto provide less consistent evidence regarding impacts of knowledge spillovers on firm performance in innovation (Jaffe et al., 1993; Almeida and Kogut, 1997; Cincera, 1997). On the one hand, benefit of knowledge spillovers from industrial agglomerations depend on whether firms are industry leaders or not (Shaver and Flyer, 2000), whether firms have sufficiently high capabilities, or the kinds of activities firms perform (Alcácer, 2006). Alternatively, R&D activities of neighboring firms may bring two countervailing effects: a positive effect from technology spillovers and a negative business stealing effect from product market rivals. Using panel data on U.S. firms, Bloom et al. (2007) find that encouraging technology spillovers dominate depressing product market spillovers.

This study contributes to filling the gap in related literature with complementing evidence. Using a survey dataset of Finnish and Swedish firms over 2002-2005, this paper considers regional human capital, firms' membership in industrial agglomerations, and empirical measurement of knowledge spillovers as alternative inputs in the modified KPF. Since two thirds of Finnish and Swedish firms have zero patent applications, and the realizations are highly dispersed, this paper applies Zero-inflated count models equipped with a "dual regime" data generating process.[3] One major advantage is that the probability of zero patents being underestimated can be avoided.

This paper finds that firm size, the R&D intensity and regional human capital are main attributes to firm innovative output. However, agglomeration of firms in proximity may not be overwhelmingly effective across all locations and industries in intensifying the production of patents. Knowledge spillovers generally bring positive

[3] See Winkelmann (Ch. 6, 2008) for a comprehensive presentation.

influences on firm patenting, while the business stealing effect within a region can counteract the local spillovers effect on firms' likelihoods to apply for a patent. Using the Information Technology (IT) industry as a reference group, firms in the Biological-Pharmaceutical (Bio-Pharm) and Automobile industries, but not in the Telecommunication (Telecom) industry, apply for more patents when more R&D is performed by other firms in proximity.

Section 2 illustrates the determinants of patenting considered in the modified KPF and related literature backgrounds. Section 3 describes the data and econometric methods applied for examining the relationships between innovation, industrial agglomeration and knowledge spillovers. Section 4 provides summary statistics of variables employed and empirical results. The concluding remarks are in section 5.

2. Determinants of Patenting

This paper modifies the traditional KPF by including innovation inputs extensively discussed in the literature as contributing factors in explaining patent production. The determinants of patenting such as measures of regional human capital, firms' membership in industrial agglomerations, and empirical measurement of knowledge spillovers along with literature background are described in the following subsections.

2.1 Regional Human Capital

Research universities provide proximate firms an important linkage to the regional infrastructure that effectively promotes knowledge overflows via hiring talents, transferring technology, placing students in industry, and a supportive platform for firms, individuals and institutions to closely interact (Florida and Cohen, 1999). Existing studies have identified that regions with strong research universities are better able to attract and support innovative industries than other regions (Saxenian, 1994; Acs et al., 1994; Audretsch and Feldman, 1996; Feldman and Audretsch, 1999). The growing importance of network-type innovation interactions among firms and private and public research institutions has attracted the attention of researchers during the last two decades (Etzkowitz & Leydersdorff, 2000). Regions with more students at advanced educational levels can be perceived as an indicator of better regional innovation potential and thus a possible determinant of firm patenting.

2.2 Industrial Agglomerations

Industrial agglomerations, portraying as a prominent feature of geography of economic activities (Krugman, 1991), can be defined as groups of proximate firms

belonging to the same industry or closely related industries. Agglomerate firms either have close buyer-seller relationships with collocating firms in other industries, or share a specialized labor pool that provides them with competitive advantage over the same industry in other places (Hill and Brenna, 2000). Even after controlling for the geographic concentration of production, innovative activities are more likely to cluster in industries where industry R&D, skilled labor, and university research are important inputs (Audretsch and Feldman, 1996). The association between innovation and agglomeration is thus broadly alleged in gaining accesses to market information, advanced human capital, and specialized value chains. Innovation activities in various industries are concentrated geographically since innovative firms are inclined to locate in areas where required resources accumulate alongside earlier regional successful experiences in innovations (Feldman, 1994). The hypothesis of positive impacts of industry agglomerations proposed in the theory of economic development suggests that agglomeration of firms or industries may lead to product or production process innovations due to intense local competition or the density of suppliers and customers (Hill and Brennan, 2000). Belonging to industrial agglomerations is essential to new product or process developments in collocating firms' shaping and realizing advantages of agglomeration economies (Hall et al., 1999).

Several empirical studies use firm level data to examine how spatial agglomerations matter in determining innovation capabilities of firms in successfully assimilating necessary knowledge. Using a dataset of 248 British firms over a 7-year period, Baptista and Swann (1998) find that innovation is greater for firms in clusters than those in isolated areas. Similarly, Cainelli and De Liso (2005) have a look at a sample of Italian firms and suggest that a favorable environment in an industrial district can be essential to product innovations of its members. However, Beaudry and Breschi (2000), analyzing a large sample of Italian and British firms over 1988-1998, demonstrate that industrial agglomerations per se do not explain all of firm innovative performance. Empirical studies up till now provide ambiguous evidence regarding the relationship between industrial agglomerations and firm innovative performance. This paper considers individual firm's membership in industrial agglomerations as an alternative explanation for patent production.

2.3 Knowledge Spillovers

Applying the model of the KPF, Jaffe (1989), Audretsch and Feldman (1996), and Feldman and Audretsch (1999) indicate that the knowledge spillovers from university labs are useful to the creation of commercial innovations by proximate firms. Black (2005) stresses the importance of geographic proximity to knowledge sources and knowledge spillovers from the presence of research universities and industrial R&D

labs in innovation processes for small firms. Given the sufficient informal information spillovers (Jaffe et al., 1993; Almeida and Kogut, 1997) and the information transfers associated with local inter-firm labor mobility (Simpson, 1992), we may gauge that external net benefits of localization more than compensate for congestion costs associated with industrial agglomeration.

However, there are concerns regarding knowledge spillovers per se and the inconsistent effects brought up. First of all, spillovers may or may not take place due to variations in technological and geographical opportunities with regions (Cincera, 1997). Second, firms benefit more from knowledge spillovers provided they have strong capability and performance in R&D activities (Alcácer, 2006). While, industry leaders may gain little in that they suffer more from knowledge spillovers to competitors in proximity (Shaver and Flyer, 2000). Third, investments in generating new knowledge by proximate firms may increase knowledge stocks of collocating firms through spillovers. But, a negative business stealing effect from rivals' innovation could lead to a more competitive market and as a result the innovation rents for a firm becomes lower. By using Compustat and U.S. patent data between 1980 and 2001, Bloom et al. (2007) find significant "strategic effects" from product market competition and even more important "spillover effects" from firms in close technological spaces. Finally, even if the importance of knowledge spillovers is acknowledged, the geographic boundary of such spillovers has been debatable (Audretsch and Feldman, 2003). The question is whether geographic distance matters in disseminating knowledge.

The contradictory findings from recent studies on the effects of knowledge spillovers may attribute partially to the difficulties in measuring knowledge dissemination empirically (Rosenthal and Strange, 2004). A typical method is to measure the knowledge stock available to an individual firm as a sum or a weighted sum of R&D stocks invested by other proximate firms. This paper provides intra- and inter-region (decaying with distance) measurements for assessing within-region as well as cross-region effects of knowledge spillovers. Subsequently, this paper not only empirically inspects the importance of knowledge spillovers but also tests whether knowledge spillovers are geographically bounded.

Carlino et al. (2007) demonstrate that patent intensity is positively related to employment and knowledge worker density across metropolitan areas in the US. It implies that local knowledge transmission could be facilitated by regional knowledge accessibility characterized by job mobility, educated human resources, and regional innovation capability. To better identify local knowledge spillovers, alternative measures can be established by weighing the R&D stocks of other neighboring firms by proxies of regional knowledge accessibility.

Inspired by literature on innovation and localized knowledge spillovers, this paper modifies the traditional KPF by including measures of regional human capital, firms' membership in industrial agglomerations, and empirical measurement of knowledge spillovers apart from other standard inputs of innovation. The augmented KPF model can be represented as:

$$Y_{it} = RD_{it}^{\beta_{RD}} EDU_{R_i t}^{\beta_{EDU}} ICD_{R_i i}^{\beta_{ICD}} RKS_{it}^{\beta_{RKS}} v_{Rit}^{*} \quad (1)$$

where Y denotes a proxy for innovative output, such as patent counts; RD is existing R&D stock; EDU is regional human capital, for instance, regional provision of university graduate students; ICD is firms' membership in industrial agglomerations, and RKS represents a variety of measures of knowledge spillovers from proximate firms or regional innovation activities, with v^{*} denoting an independent and identically distributed error term. The unit of observation for estimation is at the firm level, i at time t.

3. Data and Econometric Methods

This study uses firm level data from the 2006 EU Industrial R&D Investment Scoreboard (EUIRD) released by the Eurostat.[4] The Scoreboard provides information on the 66 Finnish firms and 81 Swedish firms investing largely in R&D. The annual figures of R&D investments, number of employees, and net sales are disclosed for the period of 2002 to 2005. This study merges records of patent applications in European Patent Office (EPO), recorded by priority year, with the firm level data of the EUIRD survey. In addition, this study combines different sources of regional data so that regional human capital, intra- and inter-region knowledge spillovers and membership in industrial agglomerations at firm level can be measured and identified. Various annual issues of the Eurostat Regional Yearbook report regional data on the number of students with advanced degrees (both master and Ph.D. program.),[5] employment,

[4] EUIRD reports company information of the top R&D investors in EU and non-EU countries. From companies' publicly available audited accounts and annual reports, the Scoreboard provides R&D figures and other economic and financial data. Source website: http://nui.epp.eurostat.ec.europa.eu/nui/show.do?dataset=rd_scb_inv

[5] Higher education is defined by the International Standard Classification of Education (ISCED) as a tertiary program, including level 5A, 5B and 6. ISCED 5 is equivalent to U.S. bachelor or master's degree. ISCED level 6 is equivalent to U.S. Ph.D. doctoral program. Data source: http://nui.epp.eurostat.ec.europa.eu/nui/show.do?dataset=educ_renrlrg1

and patent applications. The definitions of geographical units of observation are specified in line with the classifications of the Nomenclature of Territorial Units for Statistics level 2 (NUTS 2).[6] This paper identifies industrial agglomerations using the European Cluster Observatory's (ECO's) definition of regional clusters.[7]

3.1 Firms' Membership in Industrial Agglomerations

The classifications of NUTS 2 suggest that there are eight regions in Sweden and five in Finland (see Table 2). Stockholm, Sweden is in SE11, while Helsinki, Finland is in FI18. Firms are classified into different industries using their Industry Classification Benchmark (ICB) codes. According to ICB codes and the ECO's regional clusters, firms in the dataset are grouped into 11 subsamples, as listed in Table 3. The dummy SE11_IT is assigned a value of one if IT industry firms are located in region "SE11". Due to data availability, this study ignores regions in SE21, SE22, SE31, SE32, SE33, FI13, FI1a and FI20. Instead, this study includes a renowned food industry agglomerating in FI18 region as discussed in Hermesniemi, et al. (1996).

3.2 Measures of Knowledge Spillovers

Several measures of knowledge spillovers are proposed in this study. The measure of cross-region spillovers for firm i in region R_i assesses inter-regional knowledge pool contributed from firms in regions other than R_i. It is computed as a weighted sum of regional R&D stocks.

$$RKS_{it}^{E} = \sum_{R_k \notin R_i} \omega_{R_k} RDS_{R_k t}$$

where $RDS_{R_k t}$ denotes the total R&D stock of region R_k at time t. The weight ω_{R_k} is calculated as the inverse of driving time between the region R_i and the other region, R_k.

To gauge the externality of R&D activities performed by proximate firms, the intra-region (within-region) spillovers can be measured as:

$$RKS_{it}^{L} = \sum_{j \neq i,\, j \in R_i} RDS_{jt}$$

where RDS_{jt} denotes the stock of R&D expenditures for neighboring firm j in region

[6] The NUTS developed by Eurostat provides level 2 and level 3 uniform breakdowns of territorial units for constructing EU's regional statistics. Due to data availability, this paper uses the NTUS 2 definition.

[7] For more details of the methodology of cluster classification in the ECO, see the website http://www.clusterobservatory.eu/index.php?id=1&article=25&nid.

R_i at time t. Since local knowledge transmission can be fostered by job mobility, educated human resources, and regional innovation capability, alternative knowledge spillovers measures can be established by interacting RDS_{jt} with proxies for regional knowledge accessibility. Jobs per square kilometer, patent applications per million inhabitants, or ratio of post-graduate students to the total population can be used as interaction terms for constructing additional knowledge spillovers measures, *JDKSL*, *PAKSL*, and *EDKSL* respectively. For example,

$$JDKSL_{tt} = \sum_{j \neq i, j \in R_i} \theta_{R_i t}^{JD} RDS_{jt}$$

where $\theta_{R_i t}^{JD}$ denotes the job density of region R_i.

3.3 Econometric Methods

In practice, firms do not always apply for patents since their R&D activities are complicate and risky. Hence, the literature on innovation often encounters datasets that include large numbers of zeros, which creates a problem for traditional count regressions. In the case of Finnish and Swedish firms presented here, 67% of the observations have zero patent counts (see Table 1). The range of number of patent applications varies widely from zero to 727 counts. As shown in Figure 1, the distributions of patent counts truncated at 30 for 147 Finnish and Swedish firms are displayed consistently during the sample periods. In particular, due to high proportions of zeros and lengthy right tails, there are low median values and high means. Highly skewed patent counts data may be attributed to R&D investment, unobserved heterogeneity such as differences in patent innovation quality, and likely random components (Gurmu and Fidel, 2008).

Since the traditional count data model is likely to under (or over) estimate the theoretical probability of zeros. To analyze the discrete and non-negative patent count data associated with an unobserved firm heterogeneity and to illuminate the distinctive patent characteristic of “excess zeros”, the Zero-inflated count data models are presented and highlighted. The mechanism underlying the Zero-inflated count data model regarding how zero is generated may arise from two simultaneous decisions. The Zero-inflated Poisson (ZIP) model (Mullahy, 1986; Lambert, 1992) is represented as:

$$Y_{it} = 0 \text{ with probability } \omega_{it}$$
$$Y_{it} \sim Poisson(\lambda_{it}) \text{ with probability } 1 - \omega_{it}.$$

The zero and positive outcomes thus can be expressed as:

$$\Pr[Y_{it} = 0] = \omega_{it} + (1 - \omega_{it}) g_{it}(0),$$
$$\Pr[Y_{it} = k > 0] = (1 - \omega_{it}) g_{it}(k),$$

where $g_{it}(\cdot)$ is a regular count data Poisson probability function and can be specified as $\log(\lambda_{it}) = \alpha_i + x_{it}^{'}\beta,$ and k is a positive integer. The data generation process involves two states in the ZIP model, a zero state in which only zero outcomes are observed and a Poisson state in which all the nonzero outcomes and a few of the zeros outcomes are observed. The ZIP model thus can differentiate marginal probability effects at the extensive and intensive margins. Replacing $g_{it}(\cdot)$ with a Negative Binomial probability function, the specification becomes a Zero-inflated Negative Binomial (ZINB) model. Clearly the ZINB model nests the ZIP model even though the ZIP is not nested with the standard Poisson model.[8] Notably, the probability ω_{it} can either be a constant (that is, $\omega_{it} = \omega$) or can be specified as a logit model, such as $\omega_{it} = \exp(z_{it}^{'}\gamma)/(1+\exp(z_{it}^{'}\gamma)).$[9]

4. Summary Statistics and Empirical Results

The dependent variable, the number of patent applications filed by firm *i* at time *t*, is assumed to be an independently distributed Poisson (or Negative Binomial) distribution with a parameter, λ_{it}, depending on a set of explanatory variables. An empirical counterpart of the augmented KPF model can be expressed as:

$$\log(\lambda_{it}) = \beta_0 + \beta_1 LogRDINT_{it} + \beta_2 LogL_{it} + \beta_3 LogEDU_{R_i} + \beta_4 LogRKS_{it}^{E} + \beta_5 LogRKS_{it}^{L} + \sum_{m=2002}^{2004}\phi_{\mathrm{m}} TD_m + \sum_{\mathrm{l}=1}^{3}\gamma_1 ID_l + \sum_{\mathrm{n}=1}^{11}\theta_{\mathrm{n}} ICD_n + \varepsilon_{it}, \quad (3)$$

where parameters β's are coefficients of elasticity. *LogRDINT*, the R&D stock intensity in logarithmic form, is the cumulated R&D investments with an assumed 15% depreciation rate per dollar of sales. *LogL*, the number of employees in logarithmic form, is a proxy for firm size. $LogEDU_{Ri}$, the logarithmic of students with post-graduate education in region R_i, indicates regional human capital. $LogRKS^E$ is the logarithmic of measure of cross-region knowledge spillovers, and $LogRKS^L$ is the logarithmic of measure within-region knowledge spillovers. Notably, RKS^L may have various specifications, as discussed in Section 3. The dummy variables ID_1, ID_2, ID_3 designate a value of one to the industry of Bio-Pharm, Automobile, and Telecom

[8] Vuong (1989) proposes a test statistic for distinguishing non-nested models.

[9] It is worth noting that the set of variables z_{it} may or may not share variables with x_{it}. Even though z_{it} overlaps x_{it} perfectly, we still have two sets of parameters, i.e. $\beta \neq \gamma$.

respectively, where the IT industry is a reference group.[10] The dummy variables TD_m and ICD_n indicate time (2002-2005) and firms' membership in industrial agglomerations respectively.

4.1 Summary Statistics

Interpreting positive patent counts as cases of "innovation", and zero patent counts as cases of "no innovation", this study identifies 192 cases of innovation, representing roughly one third of the 586 full panel observations (see Table 4.1). Firms in the dataset are classified into 11 regional clusters which are identified by the ECO as major regions with innovation potential.[11] It is reasonable to expect that the innovative performance of inhabited firms may be more active within these regions. In aggregate, some 58% of these innovation cases are generated by firms belong to these regional clusters, exceeding the 52% of the full panel. Disaggregating the innovation distribution by regions, Table 4.2 reveals that firms patenting activities are relatively more concentrated in SE11 than in FI18.

Table 5 reports summary statistics of the variables involved in the full sample and two sub-samples. The significant standard deviations of patent counts suggest over-dispersion in both the full and sub-samples of innovation cases. The intensity of R&D stock and the firm size in innovation cases have higher sample means and standard deviations than in cases without innovation. As for other explanatory variables, their means are slightly higher in innovation cases than in no innovation cases.[12]

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[10] The ICB codes listed under the IT industry include 2733 (electrical components & equipment), 2737 (electronic equipment), 9533 (computer services), 9537 (software), 9572 (computer hardware), and 9576 (semiconductors). The Telecom industry includes 653 (fixed line telecommunications) and 9578 (telecommunications equipment). The Bio-Pharm industry includes 453 (Health care equipment & services), 4573 (biotechnology), and 4577 (pharmaceuticals). The Automobile industry includes 277 (industrial transportation), 335 (automobiles & parts), and 2753 (commercial vehicles & trucks).

[11] ECO uses Regional Innovation Statistics (RIS) to differentiate between regional clusters in high innovation environments from clusters in low innovation environments. Source website: http://www.clusterobservatory.eu/index.php?id=2&nid=

[12] A table of a correlation matrix of explanatory variables considered in this study is available from the authors upon request. There is no apparent evidence of multi-collinearity among the explanatory variables.

4.2 Model Specification Test and Results

The standard probability models are not nested in the Zero-inflated models. Vuong (1989) develops a proper test for selecting between non-nested models. The Zero-inflated models are supported when the Vuong test statistics are significantly positive, while the standard probability models are favored when the Vuong test statistics are significantly negative. Table 6 reports the Vuong test statistics of the ZIP (ZINB) as 3.92 (2.89), exceeding the 5% critical value, 1.96. The Zero-inflated models consistently exhibit better fit than the standard Poisson and Negative Binomial models since the incidence of zero patents is more frequent than that in the standard Poisson or Negative Binomial distribution. The supplementary evidence of model selection between non-nested models could be demonstrated by likelihood-ratio (LR) tests, Akaike information criterion (AIC) and Bayesian information criterion (BIC).[13] The results of LR test, AIC, and BIC reported in Table 6 suggest that the ZINB model fits better than the ZIP model for the dataset studied.

The ZINB model involves a "dual regime" data generating process, in which a Logit selection model specifies whether a firm applies for patents or not (zero state), and a Negative Binomial count process models frequencies of patent application. Coefficients estimated in the Negative Binomial regression illustrate the influences of explanatory variables on the extent to which firms engaging in patenting, while those estimated in the logit selection regression capture the impacts of the same covariates on the likelihood of firms taking no action in patent applications. Notably, the estimation of a significantly negative (positive) coefficient in the logit regression indicates increased (reduced) firm likelihood of applying for patents, which is consistent with a significantly positive (negative) coefficient estimated in the Negative Binomial regression.

Empirical results of the ZINB models are the focus of our presentation. Table 6 shows that steady R&D efforts play a positive role in explaining the likelihood and intensity of firm patenting. This study confirms that size matters because big firms are more likely to patent and patent more intensely in the innovative Finnish and Swedish regions. Using the IT industry as the reference, firms in the Telecom industry patent more intensely, but not firms in the Bio-Pharm and Automobile industries. The results shown in Table 6 suggest that Finnish and Swedish firms' innovative performances in terms of patent applications vary notably across different industries.

Controlling for firm characteristics, the empirical relationships between intensity and likelihood of patent applications and firms' membership in industrial

[13] However, the Akaike and Bayesian model selection criteria could be unsatisfactory if both models are not correctly specified (Genius and Strazzera, 2002).

agglomerations imply that industrial agglomerations may or may not improve firms' innovative performance. Table 8 reports that firms belonging to industrial agglomerations such as SE11_IT, SE23_Auto, FI18_IT, FI18_Tele, FI18_Food, and FI18_Mach produce more patents than firms in isolated areas or regional clusters not identified by the ECO. However, firms in SE12_Metal and FI19_Forest patent less intensely than firms in relatively remote areas. As in Beaudry and Breschi (2000), this study finds that industrial agglomeration itself is not overwhelmingly effective across various regions and industries in encouraging patent applications of Finnish and Swedish firms. On the other hand, Table 6 to 8 consistently reveal that regional human capital significantly raise firm patenting intensity, indicating firms in areas with abundant high quality human capital are more active in invention than those in areas lacking resources of high quality workers.

On effects of knowledge spillovers, the empirical results in Table 6 to 8 suggest that our measures of cross-region knowledge spillovers are positively associated with the Finnish and Swedish firms' intensities of patenting. The externality of knowledge dissemination could reach beyond the geographic boundary of a NUTS 2 region, which may imply that knowledge spillovers are not geographically bounded. Anselin et al. (1997) assert similarly that an effective functional region for knowledge spillovers may spread out its influence beyond the specified geographic boundary. It is shown in Table 6 that the un-weighted measure, RKS^L, is insignificant in explaining the patent production, suggesting that the "strategic effects" from product market competition and "spillover effects" from firms in close geographic space could countervail each other in magnitudes.

To better identify localized knowledge spillovers, alternative measures are calculated by interacting the R&D stock of other neighboring firms with proxies of regional knowledge accessibility. The empirical results of various measures of intra-region knowledge spillovers are presented in Table 7. Finnish and Swedish firms create less patents in regions with highly dense job offers even though there are favorable knowledge spillovers. One possible explanation is that skilled workers tend to be footloose in the sense that they can easily move between jobs taking their accumulated skills and know-how with them to competitors (Hirschman, 1970). Regions with a high job density may speed up job mobility, and accordingly chances of losing skill workers to rivalries may hurt firm's likelihood of patenting.

Alternative explanatory variables are considered in Table 8 for checking robustness of the model estimation. Empirical studies on knowledge externalities have primarily focused on the spatial dimension, however knowledge spillovers may differ substantially across industries (Feldman, 1994; Audretsch and Feldman, 1996). We interact RKS^L with three industrial dummies, ID_1, ID_2, and ID_3, indicating the

Bio-Pharm, Automobile and Telecom industries respectively. Using the IT industry as a reference industry, Table 8 shows significant and positive intra-region spillover effects for firms in the Bio-Pharm and Automobile industries, while firms in the Telecom industry experience negative intra-region spillover effects. The likelihood of invention can be positively associated with the level of research conducted. However, once competitors introduce more technologically advanced goods, sales of existing goods reduce and the goods ultimately become obsolete. Hence, the counter-intuitive empirical result could be explained by the more prevailing rivalry competition from Telecom firms in close proximity than those from IT firms. Furthermore, Shaver and Flyer (2000) suggest that industry leaders tend to gain little from externality of knowledge spillovers due to their employees defecting to competing firms, and possibly taking technologies with them.[14] Therefore, once a negative business stealing effect outweighs a positive technology spillovers effect, the aggravating market competition and lower innovation rents could reduce intensity of patent production (Bloom et al., 2007).

5. Concluding Remarks

In comparison with the other EU members and major global R&D countries, Sweden and Finland have more intense R&D investments as well as effective innovation. They also occupy strong niche positions in several industrial sectors, including information and communication technology, automobile, life sciences, forestry, renewable energy and polar research. This paper is set to provide insights on the interactions between innovative activities and industrial agglomeration, especially about the role of knowledge spillovers as a potential source of externalities in facilitating innovative performance of Finnish and Swedish firms.

By assessing determinants of propensities and intensities of patenting for Finnish and Swedish firms, this paper contributes to filling the gap in related literature with complementing evidence. Using a survey dataset of 147 Finnish and Swedish firms over 2002-2005, this paper modifies the conventional KPF model by incorporating regional human capital, firms' membership in industrial agglomerations, and empirical measurement of knowledge spillovers as alternative inputs in explaining firm innovative performance at firm level. Since two thirds of Finnish and Swedish firms have zero patent applications causing highly dispersed distributions of patent counts, this study applies the Zero-inflated Negative Binomial count models to cope

[14] Nokia and Ericsson are telecommunication companies locating in FI18_Tele and SE11_Tele respectively. Their R&D investments and patent applications are as high as $3.98 billion with 727 patents and $2.73 billion with 419 patents in 2005.

with the “excess-zeros” problem.

This paper finds that the number of patents a firm can produce increases with firm size, the R&D intensity and regional human capital. However, industrial agglomerations may not be entirely effective across all the industries and regions examined in stimulating agglomerate firms’ patenting. Inter-region knowledge spillovers may raise the patent intensities of Finnish and Swedish firms, while the effects of intra-region knowledge spillovers may be favorable or adverse depending on the industries investigated. Compared with firms in the IT industry, firms in the Bio-Pharm and Automobile industries, but not in the Telecom industry, apply for more patents when more R&D activities are performed by other proximate firms.

This study implies that pro-innovation regional policies can involve promoting steady R&D investment, nurturing highly skilled and educated manpower, and stimulating knowledge spillover activities. Regarding whether policy efforts should encourage industrial agglomerations, this study provides mixed evidence. Firms in more than half of eleven regional clusters produce more patents, yet two regional clusters have fewer patents than firms in remote areas or regions unidentified by the ECO. Therefore, subsidies for firms toward geographical concentration could encourage less innovative firms to agglomerate rather than attract more innovative firms to collocate. However, this policy implication hinges critically on the firm level data from EUIRD. The limited data availability may restrain the applicability of our empirical results in forming general policy suggestions.

Some discrepancies exist between the empirical results and the theoretical predictions. For example, the effects of within-region knowledge spillovers on innovation are not completely identified by taking regional knowledge accessibility into account. An alternative measure of local knowledge transmission may be legitimate if it can better specify proximity advantages of regional networking. The use of patent applications to measure innovation output remains debatable. On the one hand, not all patentable innovations are patented. On the other hand, firms may possibly apply for more patents than necessary to increase the market entry barriers to competitors. Additionally, patents have variable economic impacts. Exploring alternative sources of patent data other than patent counts may be essential for better measuring firm innovativeness.

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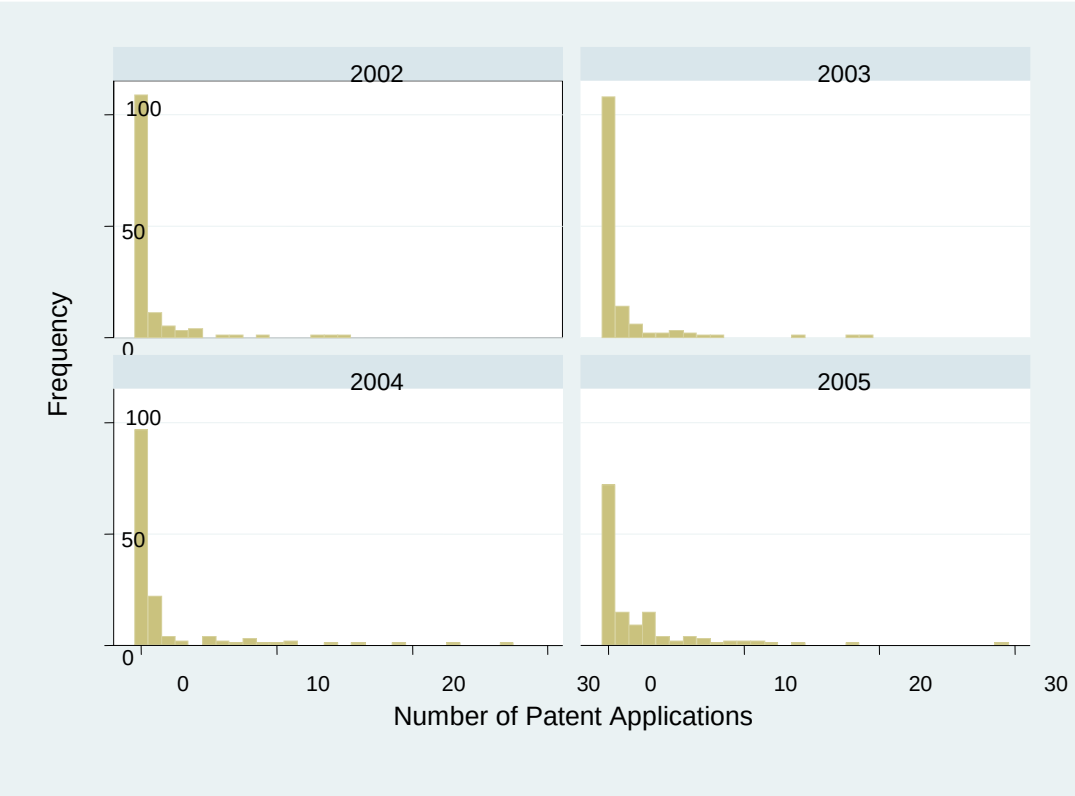
Figure 1 Distribution of Patent Applications, 2002 -2005



Source: European Patent Office

Table 1 Frequencies: Annual Number of Patents Applied by Firms, 2002-2005

Number of patents	Frequency	%
0	386	66.78
1	62	10.73
2	24	4.15
3	22	3.81
4	10	1.73
5	9	1.56
6	9	1.56
7	6	1.04
8	5	0.87
9	4	0.69
10	3	0.52
11-20	16	2.77
21-30	5	0.87
31-40	2	0.35
41-50	4	0.69
51-100	3	0.52
101-200	5	0.87
200+	3	0.52
Total	578	100

Table 2 The Eurostat NUTS 2 Classification of Regions in Finland and Sweden

Sweden	Finland
SE11 Stockholm	FI13 East Finland
SE12 East Middle Sweden (Ö stra Mellansverige)	FI18 South Finland
SE21 Småland and the islands (Småland med öarna)	FI19 West Finland
SE22 South Sweden (Sydsverige)	FI1A North Finland
SE23 West Sweden (Västsverige)	FI20 Aland
SE31 North Middle Sweden (Norra Mellansverige)	
SE32 Middle Norrland (Mellersta Norrland)	
SE33 Upper Norrland (Ö vre Norrland)	

Source: http://ec.europa.eu/eurostat/ramon/nuts/codelist_en.cfm?list=nuts.

Table 3 Regional Industrial Clusters in Sweden and Finland

Industrial Clusters	Regions				
	SE11	SE12	SE23	FI18	FI19
Information Technology	SE11_IT			FI18_IT	
Industrial Machinery				FI18_ Mach	
Telecommunication	SE11_Tele			FI18_Tele	
Forestry & Paper				FI18_Fore	FI19_Fore
Food				FI18_Food	
Industrial Metals & Mining		SE12_Metal			
Automobile			SE23_Auto		
Bio-Pharm	SE11_Bioph				

Source: European Cluster Observatory

Table 4.1 Innovation Concentration of Industrial Clusters in Sweden and Finland

	Inhabitants		Non-inhabitants		Sub-total	
	obs	ratio	obs	ratio	obs	ratio
Innovation	112	58.3%[a]	80	41.7%[a]	192	33.2%[c]
No-innovation	188	48.7%[b]	198	51.3%[b]	386	66.8%[c]
Sub-total	300	51.9%[c]	278	48.1%[c]	Full Panel: 578	

[a] The ratios are percentages of obs. in cases of innovation (192).

[b] The ratios are percentages of obs. in cases of no-innovation (386).

[c] The ratios are percentages of obs. in full panel (578).

Table 4.2 Regional Innovation Distribution in NUTS 2 Level

	Innovation		No-innovation		Sub-total	
	obs	ratio	obs	ratio	obs	ratio
SE11	65	38.2%[d]	105	61.8%[d]	170	29.4%[e]
SE12	12	37.5%	20	62.5%	32	5.5%
SE21	0	0.0%	16	100.0%	16	2.8%
SE22	24	35.3%	44	64.7%	68	11.8%
SE31	4	100.0%	0	0.0%	4	0.7%
SE23	12	54.5%	10	45.5%	22	3.8%
SE33	0	0.0%	4	100.0%	4	0.7%
FI13	0	0.0%	4	100.0%	4	0.7%
FI18	65	30.7%	147	69.3%	212	36.7%
FI19	8	23.5%	26	76.5%	34	5.9%
FI1A	2	16.7%	10	83.3%	12	2.1%
Sub-total	192	33.2%	386	66.8%	578	100%

[d] The ratios are percentages of obs. in cases of innovation or no-innovation in NUTS 2 region.

[e] The ratios are percentages of obs. in the full panel (558).

Table 5 Summary Statistics

Variables	Full Sample (578)		Innovation (192)		No innovation (386)	
	Mean	(s.d.)	Mean	(s.d.)	Mean	(s.d.)
PATENT	5.91	39.25	17.79	66.65	0	0
LogL	3.29	(0.85)	3.61	(0.92)	3.14	(0.77)
LogRDINT	-0.65	(0.74)	-0.58	(0.16)	-0.69	(0.75)
LogEDU	1.98	(0.18)	1.99	(0.06)	1.97	(0.20)
LogRKSE	3.86	(0.25)	3.89	(0.24)	3.85	(0.25)
LogRKSL	4.16	(0.49)	4.20	(0.44)	4.14	(0.51)
LogEDKSL	-0.67	(0.09)	-0.67	(0.08)	-0.67	(0.09)
LogJDKSL	4.06	(0.50)	4.10	(0.45)	4.03	(0.52)
LogPAKSL	6.61	(0.57)	6.67	(0.49)	6.58	(0.60)
LogBIOKSL	0.54	(1.42)	0.71	(1.61)	0.45	(1.31)
LogAUTOKSL	0.36	(1.17)	0.46	(1.31)	0.30	(1.08)
LogTELKSL	0.38	(1.20)	0.45	(1.30)	0.33	(1.15)

Table 6 Estimates of Zero-inflated Panel Count Models for Finnish and Swedish Firms

	ZIP		ZINB	
	Count process	Logit selection	Count process	Logit selection
Time Dummy	yes	yes	yes	yes
Constant	-31.72(10.18)***	4.00 (4.17)	-28.40 (9.10)***	9.00 (6.51)
Log L	2.10 (0.18)***	-1.46 (0.42)***	2.02 (0.24)***	-2.34 (0.69)***
LogRDINT	2.05 (0.28)***	-1.22 (0.47)***	2.13 (0.30)***	-2.05 (0.76)***
LogEDU	3.58 (1.39)***	-0.18 (2.00)	3.47 (1.95)*	-1.98 (2.82)
SE11_IT	0.94 (0.38)***	0.48 (0.92)	0.13 (0.55)	-12.57 (11.78)
SE11_Tele	-2.15 (1.27)*	-0.52 (1.18)	-1.30 (1.52)	-0.01 (1.44)
SE11_Bioph	2.23 (0.66)***	-1.90 (1.04)*	1.82 (0.52)***	-33.97 (2.94)***
SE12_Metal	-0.73 (0.54)	0.22 (1.01)	-0.85 (0.48)*	-0.40 (1.20)
SE23_Auto	0.13 (0.31)	-1.39 (1.76)	0.60 (0.39)*	-0.51 (1.51)
FI18_Fore	0.72 (0.87)	0.11 (0.97)	0.51 (0.61)	0.46 (1.56)
FI18_IT	1.23 (0.83)	0.37 (0.85)	0.74 (0.58)	0.58 (1.23)
FI18_Tele	-0.13 (1.05)	0.09 (0.75)	-0.13 (1.57)	0.55 (1.11)
FI18_Food	1.58 (0.91)*	-3.08 (5.37)	2.01 (0.76)***	-2.14 (2.98)
FI18_ Mach	1.92 (0.74)***	-0.50 (0.95)	1.33 (0.57)***	-26.69 (2.07)***
FI19_Fore	-0.05 (0.34)	1.14 (0.81)	0.29 (0.32)	1.13 (0.87)
BIO	-2.18 (0.91)***		-1.86 (0.57)***	
AUTO	-0.38 (0.39)		-0.81 (0.41)**	
TELE	2.61 (1.32)**		1.94 (1.36)	
LogRKSE	5.39 (1.91)***		4.88 (1.44)***	
LogRKSL	-0.29 (0.34)		-0.47 (0.38)	
Log likelihood	-931.78		-737.96	
AIC	1945.56		1559.91	
BIC	2122.12		1740.78	
Vuong Test (p-value) H_0: models are the same, H_A: ZIP vs. Poisson	3.92 (0.00)			
Vuong Test (p-value) H_0: models are the same, H_A: ZINB vs. NB			2.89 (0.00)	
LR Test (p-value) H_0: ZIP, H_A :ZINB			387.64 (0.00)	
Number of observations	548		548	

Note: Significant at 1% ***, Significant at 5% **, Significant at 10 % *.

Table 7 Estimates of Alternative ZINB Specifications for Finnish and Swedish Firms

	Specification 1		Specification 2		Specification 3	
	Count process	Logit selection	Count process	Logit selection	Count process	Logit selection
Time Dummy	yes	yes	yes	yes	yes	yes
Constant	-30.48(8.67)***	9.49 (4.68)	-30.38(7.52)***	8.41 (5.14)*	-28.09(7.64)***	9.06 (4.76)
Log L	1.99 (0.17)***	-2.40 (0.56)***	2.07 (0.17)***	-2.27(0.57)***	2.02 (0.17)***	-2.35 (0.56)***
LogRDINT	2.13 (0.21)***	-2.11 (0.63)***	2.20 (0.21)***	-1.96 (0.63)***	2.15 (0.21)***	-2.05 (0.62)***
LogEDU	2.87 (2.07)	-2.17 (2.09)	3.66 (1.79)**	-1.76 (2.29)	3.49 (1.79)**	-2.00 (2.12)
SE11_IT	-0.04 (0.32)	-12.76 (1.04)	0.23 (0.35)	-9.95 (119.06)	0.10 (0.33)**	-10.77 (147.38)
SE11_Tele	-1.45 (1.43)	0.12 (1.06)	-0.96 (1.33)	-0.03 (1.09)	-1.28 (1.35)	-0.02 (1.08)
SE11_Bioph	1.70 (0.50)***	-31.71(44.62)**	2.03 (0.52)***	-17.88(34.08)**	1.84 (0.51)***	-21.36 (1.11)**
SE12_Metal	-0.87 (0.76)	0.45 (1.11)	-1.00 (0.75)	0.39 (1.12)	-0.90 (0.75)	0.41 (1.11)
SE23_Auto	0.60 (0.50)*	-0.38 (1.72)	0.45 (0.49)	-0.59 (1.88)	0.60 (0.75)	-0.49 (1.78)
FI18_Fore	0.65 (0.57)	0.48 (1.80)	0.39 (0.59)	0.39 (1.73)	0.51 (0.58)	0.44 (1.75)
FI18_IT	0.84 (0.57)	0.63 (1.04)	0.63 (0.58)	0.54 (1.04)	0.73 (0.58)	0.59 (1.03)
FI18_Tele	0.12 (1.49)	0.76 (1.03)	0.01 (1.35)	0.50 (1.10)	-0.08 (1.39)	0.59 (1.06)
FI18_Food	2.15 (0.53)***	-2.11 (2.95)	1.90 (0.55)***	-2.32 (3.28)	2.01 (0.54)***	-2.16 (2.93)
FI18_ Mach	1.50 (0.45)***	-26.53 (397.72)	1.20 (0.49)***	-14.14 (762.57)	1.34 (0.46)***	-17.69 (1.99)
FI19_Fore	-0.24 (1.15)	1.14 (1.36)	-0.46 (1.15)	1.17 (1.35)	-0.29 (1.14)	1.14 (1.35)
BIO	-1.93 (0.47)***		-1.98 (0.47)***		-1.92 (0.47)***	
AUTO	-0.89 (0.34)***		-0.78 (0.33)**		-0.82 (0.34)***	
TELE	2.04 (1.29)		1.68 (1.20)		1.92 (1.22)	
LogRKSE	5.18 (1.13)***		4.98 (1.12)***		4.94 (1.14)***	
LogEDKSL	-0.30 (2.14)					
LogJDKSL			-0.32 (0.17)*			
LogPAKSL					-0.38 (0.29)	
Log likelihood	-739.14		-737.30		-738.20	
AIC	1562.28		1558.61		1560.39	
BIC	1743.14		1739.47		1741.26	
Number of observations	548		548		548	

Note: Significant at 1% ***, Significant at 5% **, Significant at 10 % *.

Table 8 Estimates of Alternative Specifications for Finnish and Swedish Firms

	ZIP		ZINB	
	Count process	Logit selection	Count process	Logit selection
Time Dummy	yes	yes	yes	yes
Constant	-29.49 (8.83)***	6.66 (3.93)*	-30.61 (7.87)***	8.29 (4.13)**
Log L	1.70 (0.18)***	-1.70 (0.40)***	1.57 (0.22)***	-1.84 (0.53)***
LogRDINT	1.63 (0.29)***	-1.51 (0.44)***	1.66 (0.35)***	-1.65 (0.61)***
LogEDU	2.14 (1.11)**	-1.20 (1.94)	2.36 (1.16)**	-2.02 (1.82)
SE11_IT	0.97 (0.34)***	0.61 (0.94)	0.92 (0.33)***	0.81 (1.07)
SE11_Tele	0.22 (1.19)	-0.37 (1.14)	1.13 (1.45)	-0.21 (1.17)
SE11_Bioph	0.56 (0.51)	-1.74 (0.96)*	0.22 (0.63)	-3.13 (3.84)
SE12_Metal	-0.79 (0.43)*	0.22 (0.98)	-1.01 (0.44)**	0.33 (1.03)
SE23_Auto	0.97 (0.22)***	-0.58 (1.00)	0.90 (0.21)***	-0.48 (1.10)
FI18_Fore	1.05 (0.77)	0..39 (0.97)	1.01 (0.68)	0.31 (1.25)
FI18_IT	1.43 (0.79)*	0.60 (0.85)	1.21 (0.67)*	-0.76 (0.86)
FI18_Tele	1.88 (0.83)**	0.21 (0.76)	2.09 (1.09)**	-0.02 (0.75)
FI18_Food	1.90 (0.83)**	-1.81 (1.84)	2.28 (0.81)***	-1.48 (1.88)
FI18_ Mach	2.41 (0.69)***	-0.16 (0.93)	2.21 (0.68)***	-0.17 (1.16)
FI19_Fore	-0.29 (0.30)	0.98 (0.80)	-0.54 (0.29)*	1.03 (0.84)
BIO	-15.16 (6.16)***		-16.95 (60.25)***	
AUTO	-12.71 (2.45)***		-10.30 (2.70)***	
TELE	10.80 (2.67)***		14.98 (3.07)***	
LogRKSE	5.53 (1.63)***		5.82 (1.41)***	
LogBIOKSL	3.27 (1.48)**		3.69 (1.50)***	
LogAUTOKSL	2.88 (0.57)***		2.26 (0.67)***	
LogTELKSL	-2.39 (0.71)***		-3.55 (0.90)***	
Log likelihood	-878.46		-723.26	
AIC	1842.92		1534.51	
BIC	2028.09		1723.99	
Number of observations	548		548	

Note: Significant at 1% ***, Significant at 5% **, Significant at 10 % *