

Srholec, Martin; Žížalová, Pavla

Conference Paper

Does the local milieu matter for innovation? Multilevel evidence from the Czech Republic

53rd Congress of the European Regional Science Association: "Regional Integration: Europe, the Mediterranean and the World Economy", 27-31 August 2013, Palermo, Italy

Provided in Cooperation with:

European Regional Science Association (ERSA)

Suggested Citation: Srholec, Martin; Žížalová, Pavla (2013) : Does the local milieu matter for innovation? Multilevel evidence from the Czech Republic, 53rd Congress of the European Regional Science Association: "Regional Integration: Europe, the Mediterranean and the World Economy", 27-31 August 2013, Palermo, Italy, European Regional Science Association (ERSA), Louvain-la-Neuve

This Version is available at:

<https://hdl.handle.net/10419/123955>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Does the local milieu matter for innovation? Multilevel evidence from the Czech Republic *

Martin Srholec
(martin.srholec@cerge-ei.cz)
and
Pavla Žížalová
(pavla.zizalova@yahoo.co.uk)

CERGE-EI, Prague**

Version of the 28th June 2013

53rd ERSa Congress),
Palermo, Italy, August 27-31, 2013.

Abstract

The aim of this paper is to estimate the impact of urbanization economies on the innovativeness of firm. Using a representative micro dataset derived from pooling two waves of Community Innovation Survey in the Czech Republic, we quantitatively assess the hypothesis that the local milieu directly affects firm's likelihood to innovate and that its impact differs for different kinds of firms. The results indicate that knowledge-driven urbanization economies, i.e. the quality of local innovation milieu, significantly boost the innovativeness of firms operating in that region, while several aspects of urbanization diseconomies, namely economic crime rate, have a detrimental impact. Moreover, the results confirm that the regional differences mediate impact of firm-level predictors, namely the age of firms. Younger firms benefit from the innovation milieu significantly more than more established firms. Nevertheless, the results also draw attention to limits of the existing models, methods and data.

Keywords: innovation, urbanization economies, multilevel modeling, cross-level effects, Czech Republic.

JEL: O30, R15, D21.

* We are grateful to the Czech Statistical Office for providing access to the micro data. Financial support from the Czech Science Foundation (GAČR) project P402/10/2310 on "Innovation, productivity and policy: What can we learn from micro data?" is gratefully acknowledged. All usual caveats apply.

** A joint workplace of the Center for Economic Research and Graduate Education, Charles University, and the Economics Institute of the Academy of Sciences of the Czech Republic.

1. Introduction

Not only individual characteristics, resources and capabilities of firms, but also the regional framework conditions within which they operate matter for their success in the innovation process. Admittedly this has been recognized for a long time in the various “contextual” perspectives on geography of innovation, including the concepts of innovative (or creative) milieu (Aydalot, 1986; Camagni, 1991; Cooke and Morgan, 1994), technology districts (Storper, 1992), learning regions (Florida, 1995; Asheim, 1996 and Morgan, 1997), collective learning (Capello, 1999; Lawson and Lorenz, 1999; and Keeble and Wilkinson, 1999) or localized learning (Maskel and Malmberg, 1999), which have largely converged into the study of regional innovation systems over the recent years (Cooke, 1992; Asheim and Isaksen, 1997; Braczyk, et al. 1998; Asheim and Gertler, 2004; Doloreux and Parto, 2005 and Iammarino, 2005). Nevertheless, quantitative empirical research testing multilevel hypotheses like these remains scarce.

Likewise, the literature on urbanization economies is predominantly based on aggregated data. As forcefully argued by Van Oort, et al. (2012), the literature on this topic suffers from ambiguity due to a lack of evidence on firm-level performance in agglomerations. Studies testing for knowledge-based urbanization economies using aggregated data can easily fall into the trap of the so-called ecological fallacy, i.e. deducting inferences about the innovation process, which is essentially firm-level phenomenon, on the base of inferences obtained for regions to which those individuals belong, hence confusing ecological correlations and individual correlations. Moreover, a little is known about which kinds of firms benefit from exactly which type of urbanization economies. Admittedly, the urbanization-firm performance relationship need to be studied by methods that properly address spatial and cross-level heterogeneity.

Following Srholec (2010), this paper further develops the multilevel analysis of the impact of contextual factors for innovation in firms. Using micro data from the Czech Community Innovation Survey (CIS), we assess the hypothesis that the regional innovative milieu affects firm’s innovativeness and that its impact differs for different kinds of firms. The main contribution of this paper is three-fold. First, the empirical analysis is based on three-times more extensive micro dataset, which provides considerably more representative evidence at both the firm and regional levels. Second, the local innovative milieu is represented by significantly more detailed indicators, including information on regional differences in the number of scientific articles, patents, university researchers, government research institutes, business research activities and innovation parks. Third, we examine the potential endogeneity of the observed characteristics vis-à-vis the regional random effects.

2. Data

The empirical analysis is based on a large micro dataset derived from two waves of CIS organized by the Czech Statistical Office (CZSO), which asked firms about their innovative activities over 2002-2005 and 2003-2006, respectively, i.e. over highly overlapping reference periods.¹ Since these are sample surveys, only a relatively small proportion of the respondents appear repeatedly in the data, which hinders the creation of longitudinal datasets. However, on the other hand, if pooled together they yield a highly representative sample. After omitting duplicates there are 9,735 unique observations covering almost half of the target population.²

The dependent variable is INNOV, which is a dummy with value 1 if the firm successfully introduced product or process innovation over the reference period; for more details on definitions see the Oslo Manual (OECD, 2005). The firm-level predictors are size, age and group membership of the firm.

SIZE is given by the log of employees in the initial year. Size of the firm is essential to control for, because the dependent innovation variable refer to firms having at least one innovation, so that larger firms are by principle more likely to report at least one positive answer; not mentioning other advantages of scale.

AGE of the firm given by the log of the number of years since the firm has been recorded in the business register. On one hand older firms can capitalize on resources accumulated over time, including learning-by-doing and other effects that are a function of time, but on the other hand younger firms can turn out to be more agile, flexible and indeed innovative. It will be interesting to see which of these factor prevails.³

The firms were further asked whether they are part of a group. DOMGP is a dummy for with value 1 if the firm is affiliated to a group with headquarters in the Czech Republic and FORGP is a dummy with value 1 if the firm is affiliated to a group with headquarters abroad.⁴ The group membership is important to account for, as affiliated firms can be more innovative thanks to a privileged access to technology (and finance) from the group, they

¹ Usually, this survey is repeated only every two to four years; however this time the CZSO decided to collect the data in two consecutive years in order to harmonize the reference period with CIS conducted in other European countries.

² Because of the two-year overlap between the reference periods, as the result of which answers of the same firm carry nearly an identical information, 2,587 duplicates appearing in both waves of the survey were eliminated from the sample. Hence, each firm appears in the data only once. A random procedure was used to select which observation is redundant.

³ Firms established over the reference period were eliminated from the sample, because new firms by principle need to introduce new products and processes when launching their business, and hence they are innovative by definition given the new to the firm minimum novelty requirement of the dependent variable.

⁴ Unfortunately, the questionnaire does not allow us to identify whether the domestic-based group has operations in other countries, so that this dummy covers not solely domestic groups, but also home-based multinational corporations.

can benefit from internal technology transfer and the group provides them with extended reach both organizationally and geographically.

Table 1 provides overview of the firm-level predictors. About 35% of the firms claimed to innovate over the period. There is a reasonable variety in terms of size and age of the firms. About 10% of them indicated to be part of a domestic group and about 15% of them reported to be foreign affiliates.

Table 1: Overview of the firm-level predictors (9,735 observations)

Variable	Mean	Std. Dev.	Min	Max
INNOV	0.35	..	0	1.00
SIZE	3.68	1.38	0	10.98
AGE	2.18	0.50	0	2.64
DOMGP	0.10	..	0	1.00
FORGP	0.15	..	0	1.00

In addition, we control for broad sectoral differences by dummy variables derived from the classification of firms in six groups of sectors following the OECD taxonomy of industries based on technology. In the manufacturing sector this taxonomy distinguishes between the so-called high-tech, medium-high-tech, medium-low-tech and low-tech industries (Hatzichronoglou 1997, OECD 2003, pp. 140 and 156). Only relatively recently this taxonomy has been extended to the service sector by including the category of so-called knowledge-intensive services, which covers the sectors of post and telecommunications (64), finance and insurance (65-67) and the other business activities excluding real estate and renting (72-74); NACE, rev. 1.1 codes are in the brackets. A mixed bag of other sectors not covered above, including mining and quarrying, electricity, gas and water supply and transport, constitute the residual category. More detailed sectoral classification cannot be used due to data limitations.

Finally, the location of firms is identified by the NUTS4 code. At this level the Czech Republic is divided into 91 units of which 15 are in the capital city of Prague. We have combined the latter into a single Prague region, because district borders with the capital are rather artificial and most of the regional data is reported only for the whole city. This leads to 77 regions with median population of about 110 thousand people and median area of about 1,000 km². About a fifth of firms in the sample is located in Prague. But median number of observations is 89 per region and minimum number of observations is 34 per region, which is fairly enough for obtaining robust multilevel inferences. Overall, the regional distribution of the sample is representative of the concentration of business activity in the Czech Republic.

It should be stressed that NUTS4 regions embrace historical spatial patterns dating back at least to the administrative reform introduced during the period of the Austrian Empire in

the middle of the nineteenth century and comprised the main local units of administration during the post WWII period, including the period of central planning over 1948-1989. Even after the recent regional reform, labour offices, local courts, school districts, land register offices or local police, tax and custom headquarters continue to be organized by districts. Local labour markets largely continue to follow this regional stratification, hence these regions represent relevant “poles” of economic activity.

Since we use a multilevel model, we need data specifically measured at the regional level. For this purpose we collected a set of regional indicators at the NUTS4 level that capture salient facets of knowledge-driven urbanization economies, i.e. the regional innovation milieu, and the aspects of urbanization diseconomies. To limit the influence of shocks and measurement errors occurring in specific years, we use the regional indicators in the form of three-year averages, if not specified otherwise. And to limit the possible simultaneity bias, whenever possible the regional indicators are measured before the reference period of the micro data. All of the regional variables are used in logs to limit the possible impact of outliers.⁵ Appendix 1 provides details on definitions, sources and periods of the regional data.

Yet the indicators of knowledge-driven urbanization economies tend to be highly correlated, which raises serious concerns of multicollinearity, if they were included in the estimate simultaneously. Hence, following Fagerberg and Srholec (2008) and Srholec (2010) we identify with the help of factor analysis the common root of the data, which allows us to construct a measure that can be used to represent their joint impact. Table 2 shows results of the factor analysis. Only one factor score with eigenvalue higher than one was detected, explaining 51.8% of the total variance. So-called factor loadings, which are the correlation coefficients between the indicators (rows) and the principal factor (column), are reported in the table. Since all the indicators come out with high loadings, we use the variable derived from the factor analysis, denoted by MILIEU in the following, as an indicator of the overall quality of the innovative milieu. Note that this variable comes out standardized from the factor analysis, i.e. mean of zero and standard deviation of one, with higher scores indicating more favourable milieu.

⁵ To avoid the log of zero, whenever necessary, we added unity to the figures of all observations before the transformation, hence transforming the data uniformly in space.

Table 2: Results of the regional factor analysis (factor loadings after rotation)

	Innovative milieu MILIEU
Science and engineering journal articles (per 100,000 people)	0.86
Patent applications (per 100,000 people)	0.65
Utility design applications (per 100,000 people)	0.60
Academy of sciences researchers (per 100,000 people)	0.66
University researchers (per 100,000 people)	0.79
Business R&D employees (per 100,000 people)	0.65
Innovation parks (m2 per 100,000 people)	0.51
Adult population with university education (% of age 15+)	0.91
Households with internet access (% of total)	0.82
Acquired intangible fixed assets (CZK per capita)	0.64

Note: The number of observations is 77; one factor with an eigenvalue greater than 1 was detected, which explains 51.8% of the total variance; the extraction method is principal factors.

Nevertheless, areas with high urbanization economies, i.e. areas that are too densely populated, may at the same time suffer from various congestion effects. Hence, it is important to take into also urbanization diseconomies due to crime, pollution or high real estate prices. In this respect, we use three regional indicators. CRIME refers to the number of cases of economic crimes. POLLUTE is used to control for the pollution given by SO₂ emission, of which a major source are cars. ESTATE is a proxy for land (or rental) prices given by the average price of new housing.

3. Econometric model

To handle hypotheses identified at different levels, the method of multilevel modeling has been developed in the recent econometric literature (Goldstein, 2003). A multilevel model, sometimes also called a ‘hierarchical’, ‘random coefficient’ or ‘mixed-effect’ model relates a dependent variable to predictor variables at more than one level. Suppose a logit multilevel model has 2-level structure with firms denoted by i subscript at level-1 located in regions denoted by j subscript at level-2. Given the variables in hand, the empirical multilevel model estimated in this paper can be denoted as follows:

Level-1 logit model:

$$E(\text{INNOV}_{ij} = 1 \mid \beta_j, \delta_k) = \varphi_{ij}$$

$$\text{Log} [\varphi_{ij} / (1 - \varphi_{ij})] = \eta_{ij}$$

$$\eta_{ij} = \beta_{0j} + \beta_{1j}\text{SIZE}_{ij} + \beta_{2j}\text{AGE}_{ij} + \beta_{3j}\text{DOMGP} + \beta_{4j}\text{FORGP} + \sum_{k=1} \delta_k \text{SECTOR}_{ik}$$

Level-2 model:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}\text{MILIEU}_j + \gamma_{02}\text{CRIME}_j + \gamma_{03}\text{POLLUTE}_j + \gamma_{04}\text{ESTATE}_j + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}\text{MILIEU}_j + \gamma_{12}\text{CRIME}_j + \gamma_{13}\text{POLLUTE}_j + \gamma_{14}\text{ESTATE}_j + u_{1j}$$

$$\beta_{2j} = \gamma_{20} + \gamma_{21}\text{MILIEU}_j + \gamma_{22}\text{CRIME}_j + \gamma_{23}\text{POLLUTE}_j + \gamma_{24}\text{ESTATE}_j + u_{2j}$$

$$\beta_{3j} = \gamma_{30} + \gamma_{31}\text{MILIEU}_j + \gamma_{32}\text{CRIME}_j + \gamma_{33}\text{POLLUTE}_j + \gamma_{34}\text{ESTATE}_j + u_{3j}$$

$$\beta_{4j} = \gamma_{40} + \gamma_{41}\text{MILIEU}_j + \gamma_{42}\text{CRIME}_j + \gamma_{43}\text{POLLUTE}_j + \gamma_{44}\text{ESTATE}_j + u_{4j}$$

where γ_{00} is the estimated grand average of the log-odds of firms to innovate across regions, $\gamma_{10} \dots \gamma_{40}$ are the firm-level fixed effects, $\gamma_{01} \dots \gamma_{04}$ are the direct region-level fixed effects for the intercept, $\gamma_{11} \dots \gamma_{41}$ are cross-level interaction terms between the firm- and region-level predictors and finally $u_{0j} \dots u_{4j}$ are random (or residual) effects for each of β_j , which tell us that the respective coefficients vary not only as a function of the predictors, but also as a function of unobserved regional effects; u_j are conventionally assumed to be sampled from a normal distribution with expected zero mean and variance σ_u^2 and they are assumed to be independent from the predictors and from each other. Also we control for sectoral differences by including a set industry dummies, the effects of which δ_k are however not allowed to differ by region.⁶

Since the dependent variable is binary, we need to specify a non-linear model. For this purpose, we assume a binomial sampling model and use a logit link function to transform the level-1 predicted values, where η_{ij} is the log of the odds of success. Although φ_{ij} is constrained to be in the interval (0, 1), the logit transformation allows η_{ij} to take any value

⁶ Low-tech industry is used as the base category.

and, therefore, can be substituted to the structural model.⁷ Note that only the level-1 part of the model differs from a linear case. However, there is no term for the level-1 residual in the binomial logit model because for binary dependent variables the variance is completely determined by the mean and thus a separate error term is not estimated; for more detailed explanation see Luke (2004, pg. 55).

If a hierarchical structure of data exists, multilevel models allow us to properly estimate the extent to which differences between higher-level units, such as urbanization (dis)economies at the regional level, are accountable for outcomes at a lower level, in this case for the innovativeness of firms. In addition, in a more complex model like this one, we can examine whether the regional conditions interact with the characteristics of firms. In other words, we can examine though considering the cross-level interaction terms the extent to which the impact of regional contextual differs for different kinds of firms.

Note that the reduced version of this model, where the region-level equations are substituted for β_j into the firm-level model and only the random effect for the intercept u_{0j} is allowed for, could be seen as the standard random-effects logit model. However, in the multilevel model we do not only consider the random intercept, but also allow the slope effects to be random. And we do not include $MILIEU_j$, $CRIME_j$, $POLLUTE_j$ and $ESTATE_j$ directly into the firm-level part of the model, because as soon as these variables represent a genuinely regional-level characteristic, as they truly do here, it is more appropriate to allow them to operate only at the regional-level of the model.

4. Econometric results

As discussed in more detail by Goldstein (2003), the presence of more than one residual term makes the traditional estimation procedures inapplicable and, therefore, specialized maximum likelihood estimators must be used for these models. Raudenbush, et al. (2004) developed for this purpose the hierarchical model line of estimators. More specifically, in this paper we use the estimator based on restricted maximum likelihood procedure with the logit link function. Statistical software Hierarchical Linear and Non-linear Modeling (HLM) version 6.08 was used to estimate the model.

To improve the interpretability of the results we standardize the firm-level predictors $SIZE_{ij}$ and AGE_{ij} as well as the region-level predictors $MILIEU_j$, $CRIME_j$, $POLLUTE_j$ and $ESTATE_j$ by deducting mean and dividing by standard deviation, so these variables enter the estimate with mean of zero and standard deviation equal to one. Since zero of the $DOMGP_{ij}$ and $FORGP_{ij}$ variables implies a domestic non-affiliated firm, all of the

⁷ From this follows that the predicted log-odds can be reversed to odds by $\exp(\eta_{ij})$ and to the predicted probability ϕ_{ij} by $\exp\{\eta_{ij}\}/(1+\exp\{\eta_{ij}\})$.

predictors enter the estimate with meaningful zero points, which greatly simplifies the interpretation of the estimated coefficients, especially for the intercept.

Table 3 gives the first set of results, in which we examine the so-called “intercept-as-outcome” models, i.e. we include the regional-level predictor for the intercept and allow for the random intercept, only. In the first column, we include the firm-level predictors and the region-level random effect for the intercept. In the second column, we add the regional-level predictor $MILIEU_j$ for the intercept, the impact of which is at the centre of our interest. In the third column, we control also for the impact of the other regional-level predictors $CRIME_j$, $POLLUTE_j$ and $ESTATE_j$ on the intercept. Note that the fixed effects are reported as odds ratios.

As expected, the firm-level predictors come out with odds ratios higher than one and highly statistically significant coefficients indicating that larger, more established and affiliated firms are estimated to be more likely to innovate. The pivotal finding is that the regional innovation milieu is a highly statistically significant predictor of the likelihood of firm’s to innovate. All else equal to zero, a firm operating in a region with $MILIEU_j$ one standard deviation above the mean is estimated to be 1.068 times more likely to innovate; just thanks to benefiting from the knowledge-driven urbanization economies. If we control for the other region-level predictors, this odds ratio nearly doubles indicating that a firm that is otherwise the same located in a region with $MILIEU_j$ one standard deviation above the mean is 1.128 times more likely to innovate. Also the negative impact of urbanization diseconomies is supported by the results, particularly of $CRIME_j$, although $ESTATE_j$ does not seem to make much difference.

Also the relevance of the regional innovation milieu represented by the $MILIEU_j$ indicator is supported by the fact that after this variable is included in the model, the random effect for the intercept decreases almost four times; confirming that a healthy part of the unexplained differences across regions has been accounted for. Note that the estimator provides likelihood-ratio test for the null hypothesis that the between-region variance is zero, where the p-values are based on asymptotic sampling distribution as explained by Rabe-Hesketh and Skrondal (2008, pg. 69), which is highly statistically significant in the estimate presented in the first column, thus confirming that a multilevel model is required here. Yet the null is rejected, if the region-level variables are included in the second and third estimates, thus signalling that unexplained regional variance becomes inconsequential.

Surprisingly, however, the magnitude of the random variance of the intercept is quite small, as the result of which the intra-class correlation coefficient (ICC) indicates that only a small fraction of the variability of firm-level innovativeness is accounted by regional differences; given, of course, the assumptions imposed on the random effects in the model specification.⁸ It should be noted, furthermore, that we attempted to use different regional

⁸ To calculate the ICC, we make use of the fact that the variance of the error term in a logistic regression is by assumption equal to $\pi^2/3$, hence after running a logistic multilevel model the ICC can be obtained using the following formula: $ICC = \sigma_u^2 / (\sigma_u^2 + \pi^2/3)$.

stratification hoping to achieving higher ICC for the intercept. More specifically, we used NUTS3 with 14 regions and a custom made regional stratification between NUTS3 and NUTS4 with 30 regions⁹ but the results turned out qualitatively very similar. It is well acknowledged that it may be more relevant to use smaller units than NUTS4, however, this is not possible due to data limitations, in particular confidentiality constraints.

Another diagnostic measure of multilevel models that has not been discussed so far is the so-called index of dispersion. Although logit multilevel models do not have a separate term for the level-1 error, we can calculate a level-1 error variance scaling factor that measures the extent to which the observed errors follow the theoretical binomial error distribution and therefore provides diagnostics of the non-linear specification. Index of dispersion equal to 1 indicates perfect fit between the observed errors and the theoretical assumptions. A significant over- or under-dispersion indicates model misspecification, the presence of outliers or the exclusion of an important level in the model. Less than 5% dispersion is usually seen as satisfactory. The index of dispersion is close to unity, which confirms that in this respect the estimates do not suffer from a major problem.

⁹ These 30 regions combine neighbouring NUTS4 districts on the base of our best judgement given economic, geographical and historical patterns; details on how this has been done are available from the author upon request.

Table 3: Results of the intercept-as-outcome model

	(1) HLM	(2) HLM	(3) HLM
<u>Fixed Effects:</u>			
For Intercept _{ij} (β_{0j})			
Intercept _{ij} (γ_{00})	0.442 (0.050)***	0.439 (0.053)***	0.436 (0.051)***
MILIEU _j (γ_{01})	..	1.068 (0.012)***	1.128 (0.023)***
CRIME _j (γ_{02})	0.907 (0.023)***
POLLUTE _j (γ_{03})	0.964 (0.022)*
ESTATE _j (γ_{04})	1.000 (0.024)
For SIZE _{ij} slope (β_{1j})			
SIZE _{ij} (γ_{10})	1.523 (0.030)***	1.525 (0.030)***	1.527 (0.030)***
For AGE _{ij} slope (β_{2j})			
AGE _{ij} (γ_{20})	1.084 (0.029)***	1.085 (0.029)***	1.085 (0.029)***
For DOMGP _{ij} slope (β_{3j})			
DOMGP _{ij} (γ_{30})	2.222 (0.082)***	2.199 (0.083)***	2.222 (0.081)***
For FORGP _{ij} slope (β_{4j})			
FORGP _{ij} (γ_{40})	1.705 (0.069)***	1.678 (0.069)***	1.701 (0.065)***
SECTOR _{ik} (δ_k)	Yes	Yes	Yes
<u>Random effects:</u>			
Intercept _{ij} (u_{0j})	0.128	0.034	0.013
ICC	0.0050	0.0004	0.0001
Index of dispersion	1.001	1.002	1.004
Likelihood function	-13,845.80	-13,856.67	-13,872.82
Level-1 firms	9,735	9,735	9,735
Level-2 regions	77	77	77

Note: Non-linear unit-specific model with the logit link function; restricted maximum likelihood (PQL) estimate; odds ratios and robust standard errors in brackets reported for the fixed effects; standard deviation reported for the random effect; *, **, *** denote significance at the 10, 5 and 1 percent levels.

Table 4 gives the second set of results, in which we examine the so-called “slopes-as-outcomes” models, i.e. we relate the region-level predictors to both the intercept and slopes and allow for the random slopes. In the first column, we include only the firm-level predictors but allow for region-level random effects for both the intercept and the slopes. In the second column, we add the regional-level predictor $MILIEU_j$ not only for the intercept but also examine the cross-level interaction terms thereof. Finally, in the third column, by controlling for the other region-level predictors $CRIME_j$, $POLLUTE_j$ and $ESTATE_j$ we estimate the full multilevel model outlined in the previous section, which relates the full set of region-level predictors to both the intercept and slopes and allows for all random terms.

First and foremost, the main finding of this exercise is that the random variance of the slopes is much larger than of the intercept. After allowing for the random slopes, hence considering that not only the central tendency in the data given by the intercept but also the impact of the firm-level predictors varies across regions, the estimated ICC increased more than ten times from a mere 0.5% to noticeably more tangible 6.3%. Hence, in other words, urbanization (dis)economies do not affect all kinds of firms in the same way; quite the opposite thesis seems supported by the data, namely that the impact of regional milieu largely depends on characteristics of the firms. It is therefore pivotal to take the heterogeneity of firms seriously, when considering the impact of regional differences.¹⁰

Moreover, several significant cross-level interaction terms of the $MILIEU_j$ variable have been detected in the second column, however, only one of them survived, i.e. remained statistically significant at the conventional levels, after the other regional-level variables are controlled for in the third column. More specifically, this is the cross-level interaction between the AGE_{ij} and $MILIEU_j$ variables, indicating that younger firms benefit from the regional innovation milieu relatively more than their established (longer operating) counterparts. Arguably, this is a feasible outcome as new firms are known to be at pain to acquire funding for innovation. For example, internal R&D department is often too expensive to maintain for new firms. And older firms are generally speaking in a better position to benefit from distant learning thanks to linkages (and “know-who”) that tends to accumulate over time. Hence, access to external sources of knowledge nearby can at least partly help to overcome these “disadvantage of newness”. Admittedly, this is a potent policy finding that feeds into the importance of regional milieu for innovative entrepreneurship.

¹⁰ Note that this result concords with the findings presented by Fazio and Piacentino (2010), who also detected the fact that the slope random effects tend to be far larger as compared to the regional variability captured by the intercept random effect.

Table 4: Results of the slopes-as-outcomes model

	(1)	(2)	(3)
<u>Fixed Effects:</u>			
For Intercept _{ij} (β_{0j})			
Intercept _{ij} (γ_{00})	0.446 (0.048)***	0.436 (0.050)***	0.432 (0.049)***
MILIEU _j (γ_{01})	..	1.059 (0.011)***	1.121 (0.022)***
CRIME _j (γ_{02})	0.909 (0.030)***
POLLUTE _j (γ_{03})	0.982 (0.022)
ESTATE _j (γ_{04})	0.986 (0.025)
For SIZE _{ij} slope (β_{1j})			
SIZE _{ij} (γ_{10})	1.579 (0.035)***	1.605 (0.039)***	1.614 (0.034)***
MILIEU _j (γ_{11})	..	0.964 (0.019)*	1.003 (0.028)
CRIME _j (γ_{12})	0.946 (0.056)
POLUTE _j (γ_{13})	0.991 (0.036)
ESTATE _j (γ_{14})	0.960 (0.044)
For AGE _{ij} slope (β_{2j})			
AGE _{ij} (γ_{20})	1.101 (0.033)***	1.120 (0.034)***	1.121 (0.034)***
MILIEU _j (γ_{21})	..	0.947 (0.029)*	0.915 (0.039)**
CRIME _j (γ_{22})	1.047 (0.033)
POLUTE _j (γ_{23})	0.973 (0.033)
ESTATE _j (γ_{24})	1.060 (0.044)
For DOMGP _{ij} slope (β_{3j})			
DOMGP _{ij} (γ_{30})	2.099 (0.092)***	2.210 (0.115)***	2.263 (0.116)***
MILIEU _j (γ_{31})	..	0.995 (0.059)	1.030 (0.095)
CRIME _j (γ_{32})	1.056 (0.132)
POLUTE _j (γ_{33})	0.899 (0.090)
ESTATE _j (γ_{34})	0.915 (0.109)
For FORGP _{ij} slope (β_{4j})			
FORGP _{ij} (γ_{40})	1.571 (0.066)***	1.532 (0.091)***	1.548 (0.088)***
MILIEU _j (γ_{41})	..	1.075 (0.036)**	1.036 (0.067)
CRIME _j (γ_{42})	0.998 (0.096)
POLUTE _j (γ_{43})	0.963 (0.068)
ESTATE _j (γ_{44})	1.077 (0.074)
SECTOR _{ik} (δ_k)	Yes	Yes	Yes
<u>Random effects:</u>			
Intercept _{ij} (u_{0j})	0.093	0.050	0.040
SIZE _{ij} slope (u_{1j})	0.159	0.158	0.153
AGE _{ij} slope (u_{2j})	0.163	0.163	0.155
DOMGP _{ij} slope (u_{3j})	0.326	0.414	0.449
FORGP _{ij} slope (u_{4j})	0.235	0.212	0.204
ICC	0.0632	0.0759	0.0816

Index of dispersion	0.9959	0.9976	0.9991
Likelihood function	-13,834.58	-13,858.17	-13,892.06
Level-1 firms	9,735	9,735	9,735
Level-2 regions	77	77	77

Note: Non-linear unit-specific model with the logit link function; restricted maximum likelihood (PQL) estimate; odds ratios and robust standard errors in brackets reported for the fixed effects; standard deviation reported for the random effects; *, **, *** denote significance at the 10, 5 and 1 percent levels.

Another glance at the random part of the model reveals that after the region-level predictors are included standard deviation of the slope random effects do not decrease much, which signals that a healthy part of the random variance across regions has not been accounted for. So there is still considerable unobserved diversity across regions. Some of these differences could be very difficult to ever measure properly, including expectations about the technology, economy and society at large, the extent of trust, honesty or “social” capital, whether there is “innovative culture” in the region and other latent differences. Furthermore, there can be regionally correlated measurement errors of the micro variables which collapse into the residuals too. For example, what is sufficiently “new” to qualify for a positive answer about innovation in the survey might have been perceived differently by respondents in major urban centres, such as Prague, as compared to the countryside, i.e. respondents in regions who are more “modest” in assessing their achievements might have reported less spectacular results and vice-a-versa. All that a researcher can do about this, given the imperfect data in hand, is to properly account for these unobserved (or unobservable) differences in the multilevel framework.

Finally, we test robustness of the results with regards to potential cross-level endogeneity issues. Table 5 shows results of the robustness tests. In the first column, for a comparison we present results of an ordinary model that represents the benchmark. In the second column, we present instrumental variables regression that attempt to tackle the potential endogeneity of $MILIEU_j$ with the help of historical records of regional population density and a dummy for national borders. In the third column, we test for the potential endogeneity of the firm-level regressors with regards to the random effect for the intercept. For this purpose, we switch to estimating probit models, which are more suitable, i.e. estimator of probit model with continuous endogenous regressors is not readily available. All of these estimates are conducted in Stata 11.2.

Admittedly, there is the potential inconsistency of $MILIEU_j$, as unobservable shocks affecting the firm’s propensity to innovate also affect the regional innovative milieu, which needs to be treated in the framework of instrumental variables estimate. In other words, the exogeneity of $MILIEU_j$ is under suspicion. For this purpose, we are armed with data on the past population density by region obtained from historical records that stretch as far back as more than a century ago. $POPDEN_j$ is the log of population density in the region in 1900. The rationale for using this instrument is that the historical population density reflects significantly less urbanization economies driven by the development of modern industry and knowledge infrastructure, because this is still to a large extent driven by the factors of geography and nature (landscape, access to water and soil fertility) and historical conditions (ancient settlements, privileges, wars, border shifts), etc. By using $POPDEN_j$ as the instrument of $MILEU_j$, we take out the element of knowledge-driven urbanization economies that came into existence in the previous century,

which are arguably decisive and therefore are likely to be the main source of endogeneity with regards to firm's innovativeness. In addition, we take into account the national borders. $BORDER_j$ is a dummy with value 1 for border regions. Again, this is supposed to pick up conditions that are specific to the borders and are likely to influence the knowledge-driven urbanization economies but much less the contemporary innovativeness of firms, such as resettlement of Sudeten after the WWII, the Iron Curtain on the western border during the cold war, etc. It should be pointed out that neither $POPDEN_j$ or $BORDER_j$ is statistically significant, if included in the benchmark model.

More specifically, we use a test of exogeneity for a probit model proposed by Smith and Blundell (1986). Under the null hypothesis, the model is appropriately specified with all explanatory variables as exogenous. Under the alternative hypothesis, $MILIEU_j$ is expressed as a linear projection of a set of instruments, and the residuals from those first-stage regressions are added to the model. Under the null hypothesis, these residuals should have no explanatory power. A Wald test of exogeneity of $MILIEU_j$ is reported at the bottom of the table. If the test statistic is not significant, there is not sufficient information in the data to reject the null that there is no endogeneity, which is the case here. Hence, there does not seem to be a serious bias in this respect (in fact, the estimated coefficient of $MILIEU_j$ has in the instrumental variables regression, so if anything, there is a downward bias). Furthermore, the test of overidentifying restrictions based on the seminal work by Sargan (1958), i.e. a test of the exogeneity of the instruments, does not reject the null, which confirms that the instruments are valid.

In the third column, we are concerned about the potential correlation of u_j with the firm -level predictors due to omitted explanatory variables that simultaneously affect the predictors and the region-specific residuals. Here, the potential endogeneity of the within effects of the firm-level predictors with regards to u_j can be relatively easily treated by accounting in the model for their regional means, i.e. the regional means $SIZE_j$, AGE_j , $DOMGP_i$ and $FORGP_j$, because this way they can serve as instrumental variables of themselves; for details see (Rabe-Hesketh and Skrondal 2008, pg. 115); see also Fazio and Piacentino (2010) for using the same procedure. Since none of the regional means of the firm-level predictors is not statistically significant at the conventional levels, there does not seem to be a serious bias in this respect either.

It should be stressed, furthermore, that the results do not suffer from a serious problem of multicollinearity, neither among the firm- nor region-level predictors. Among the firm-level predictors the correlation coefficient never exceeds 0.34 and among the region-level predictors the correlation coefficient does not surpasses 0.47, which confirms that these variables capture distinct characteristics.

Table 5: Results of the robustness tests

	(1)	(2)	(3)
Constant (γ_{00})	-0.510 (0.033)***	-0.513 (0.034)***	-0.484 (0.084)***
MILIEU _j (γ_{01})	0.070 (0.014)***	0.087 (0.022)***	..
CRIME _j (γ_{02})	-0.056 (0.018)***	-0.066 (0.021)***	..
POLLUTE _j (γ_{03})	-0.021 (0.015)	-0.021 (0.015)	..
ESTATE _j (γ_{04})	0.001 (0.016)	-0.010 (0.020)	..
SIZE _{ij} (γ_{10})	0.254 (0.015)***	0.254 (0.015)***	0.253 (0.015)***
AGE _{ij} (γ_{20})	0.047 (0.014)***	0.048 (0.014)***	0.046 (0.014)***
DOMGP _{ij} (γ_{30})	0.489 (0.046)***	0.487 (0.046)***	0.489 (0.046)***
FORGP _{ij} (γ_{40})	0.329 (0.041)***	0.328 (0.041)***	0.342 (0.041)***
SIZE _j (γ_{50})	0.033 (0.192)
AGE _j (γ_{60})	0.093 (0.157)
DOMGP _j (γ_{70})	0.349 (0.565)
FORGP _j (γ_{80})	-0.447 (0.339)
SECTOR _{ik} (δ_k)	Yes	Yes	Yes
u _{0j} (σ_{0j})	0.080
Rho	0.006
LR test	9.54***
LR χ^2	1,284.61***
Wald χ^2	..	1,182.10***	1,156.60***
Ln(σ)	..	-0.256 (0.007)***	..
Smith–Blundell’s statistic	..	0.98	..
Sargan’s statistic	..	0.77	..
LL	-5,639.75	-16,963.45	-5,652.06
Endogenous: MILIEU _j Excl. instruments: POPDEN _j , BORDER _j			
Level-1 firms	9,735	9,735	9,735
Level-2 regions	77	77	77

Note: Standard errors in brackets reported for the fixed effects; *, **, *** denote significance at the 10, 5 and 1 percent levels.

5. Conclusions

Many researchers have over the years evaluated the link between the regional milieu and firm's innovativeness. But papers directly confirming the spatial context of innovation on the basis of a formal quantitative analysis are scant. Using micro data in the multilevel framework, we confirmed that firm's characteristics are important for explaining innovation, but show that regional differences matter too. Size, age and affiliation to a group influence their odds to innovate, so as do benefits from location in a vibrant regional milieu. Also the results indicate that impact firm's age turns out to be intertwined with quality of the regional innovation milieu.

An important implication of the paper is that analyses of innovation on one hand and studies of urbanization economies on the other hand can greatly benefit from multilevel modeling, hence from taking more seriously into account the hierarchical nature of data. Because the underlying hypotheses are multilevel, we should use analytic methods that are also multilevel. If we do not do that, we may keep missing important part of the picture; risking to suffer from the ecological or atomistic fallacy. Of course, firms can be grouped not only spatially by regions, but also by sectors. Structure of a multilevel model may be more complicated if we wish to include more levels of the hierarchy. Also 3-level models with firms in regions within countries or so-called cross-classified models with firms in sectors and simultaneously in regions can be estimated. All that matters is the availability of suitable data for this purpose.

At last but not least, policy makers should understand and utilize the multilevel perspective if they are to be successful at promoting innovativeness of firms and ultimately regional development. It comes out from the analysis that younger firms benefit most from location in a vibrant innovation milieu. A reasonable strategy to catalyze innovation particularly in young firms, in other words to promote innovative entrepreneurship, therefore seems to be to improve the regional framework conditions. More complex and comprehensive policies need to be designed to tackle the interdependence among different levels of analysis when it comes to promoting innovativeness of firms.

References

- Asheim B.T. (1996) Industrial districts as 'learning regions': A condition for prosperity. *European Planning Studies*, 4, 379-400.
- Asheim B.T. and Isaksen, A. (1997) Location, agglomeration and innovation: Towards regional innovation systems in Norway?, *European Planning Studies* 5, 299-330.
- Asheim B.T. and Gertler M. (2004) Regional systems of innovation, in Fagerberg J., Mowery D.C. and Nelson R. (Eds) *The Oxford Handbook of Innovation*, pp. 291-317. Oxford University Press, Oxford.
- Aydalot P. (1986) *Milieux innovateurs en Europe*. GREMI, Paris.
- Basilevsky A. (1994) Statistical Factor Analysis and Related Methods: Theory and Applications. John Wiley & Sons Inc., London.
- Boschma R.A. and Frenken K. (2006) Why is economic geography not an evolutionary science? Towards an evolutionary economic geography, *Journal of Economic Geography* 6, 273-302.
- Boggs, J.S. and Rantisi N.M. (2003) The "relational" turn in economic geography, *Journal of Economic Geography* 3, 109-116.
- Braczyk H-J., Cooke, P. and Heidenreich M. (1998) *Regional Innovation Systems: The Role of Governances in a Globalized World*. Routledge, London.
- Capello R. (1999) Spatial transfer of knowledge in high technology milieux: Learning versus collective learning processes. *Regional Studies* 33, 353-365
- Camagni R. (1991) Introduction: from the local 'milieu' to innovation through cooperation networks, in Camagni, R. (Eds) *Innovation networks: spatial perspectives*, pp. 1-9. Belhaven Press, London.
- Cardoso A. R. (2000) Wage differentials across firms: an application of multilevel modelling, *Journal of Applied Econometrics* 15, 343-354.
- Cooke P. (1992) Regional innovation systems: Competitive regulation in the New Europe, *Geoforum* 23, 365-382.
- Cooke P. and Morgan K. (1994) The Creative Milieu: A Regional Perspective on Innovation, in Dodgson, M. And Rothwell, R. (Eds) *The Handbook of Industrial Innovation*. Edward Elgar, Cheltenham.
- Doloreux D. and Parto S. (2005) Regional innovation systems: Current discourse and unresolved issues, *Technology in Society* 27, 133-153.
- Evangelista R., Iammarino S., Mastrostefano V. and Silvani A. (2002) Looking for Regional Systems of Innovation: Evidence from the Italian Innovation Survey, *Regional Studies* 36, 173-186.
- Evangelista R., Iammarino S., Mastrostefano V. and Silvani A. (2001) Measuring the regional dimension of innovation. Lessons from the Italian Innovation Survey, *Technovation* 21, 733-745.
- Fagerberg, J. and Srholec, M. (2008) National Innovation Systems, Capabilities and Economic Development. *Research Policy* 37, 1417-1435.
- Fazio, G. and Piacentino, D. (2010) A Spatial Multilevel Analysis of Italian SMEs' Productivity, *Spatial Economic Analysis* 5, 299-316.
- Feldman M.P. (2000) Location and innovation: the new economic geography of innovation, spillovers and agglomeration, in Clark G.L., Feldman M.P. and Gertler M.S. (Eds) *The Oxford Handbook of Economic Geography*, pp. 373-394, Oxford University Press, Oxford.
- Florida R. (1995) Toward the learning region. *Futures* 27, 527-536.

- Fotheringham A. S., Brunsdon C. and Charlton M. (2000) *Quantitative Geography: Perspectives on Spatial Data Analysis*. Sage Publications Ltd., London.
- Goldstein H. (2003) *Multilevel Statistical Models*. Arnold, London.
- Hatzichronoglou T. (1997) Revision of the High-technology Sector and Product Classification. Paris: OECD, STI Working Paper 1997/2.
- Hox J. (2002) *Multilevel Analysis*. Lawrence Erlbaum Associates, Inc., Mahwah (New Jersey).
- Iammarino S. (2005) An evolutionary integrated view of Regional Systems of Innovation: Concepts, measures and historical perspectives, *European Planning Studies* 13, 497–519.
- Keeble D. and, Wilkinson F. (1999) Collective learning in regionally clustered high technology SMEs in Europe. *Regional Studies* 33, 295–303
- Lawson C. and Lorenz E. (1999) Collective learning, tacit knowledge and regional innovative capacity. *Regional Studies* 33, 305–317
- Luke A. (2004) *Multilevel Modeling*. Sage Publications: London.
- Maskell P. and Malmberg A. (1999) Localised learning and industrial competitiveness. *Cambridge Journal of Economics* 23, 167–185.
- Morgan K. (1997) The learning region: institutions, innovation and regional renewal, *Regional Studies* 31, 491–504.
- OECD (2003) *Science, Technology and Industry Scoreboard*. OECD: Paris.
- OECD (2005) *Oslo Manual*. 3rd edition. OECD: Paris.
- Van Oort, F.G., Burger, M. J., Knoben, J. and Raspe, O. (2012) Multilevel approaches and the firm-agglomeration ambiguity in economic growth studies. *Journal of Economic Surveys* 26, 468-491.
- Rabe-Hesketh, S., Skrondal, A. and Pickles, A. (2008) Reliable estimation of generalized linear mixed models using adaptive quadrature. *Stata Journal*, 2, 1-21.
- Rabe-Hesketh, S. and Skrondal, A. (2008) *Multilevel and Longitudinal Modeling Using Stata*. Stata Press, 2nd edition.
- Raudenbush S., Bryk A., Cheong Y. F., Congdon R. and du Toit M. (2004) *HLM 6: Hierarchical Linear and Nonlinear Modeling*. Scientific Software International, Lincolnwood.
- Sargan, J.D. (1958) The Estimation of Economic Relationships Using Instrumental Variables. *Econometrica* 26, 393-415.
- Smith, R. J. and Blundell, R. W. (1986) An exogeneity test for a simultaneous equation Tobit model with an application to labor supply. *Econometrica*, 54, 679-686.
- Srholec M. (2010) A Multilevel Approach to Geography of Innovation, *Regional Studies* 44, 1207-1220.
- Storper M. (1995) The Resurgence of Regional Economies, Ten Years Later: The Region as a Nexus of Untraded Interdependencies. *European Urban and Regional Studies* 2, 191-221.

Appendix 1: Overview of the regional variables

<i>Definition</i>	<i>Unit</i>	<i>Source</i>	<i>Reference period</i>
Science and engineering journal articles	per 100,000 people	R&D&I Information System of the Czech Rep.	2000 & 2002
Patent applications	per 100,000 people	Industrial Property Office	2000-2002
Utility design applications	per 100,000 people	Industrial Property Office	2000-2002
Academy of sciences researchers	per 100,000 people	Academy of Sciences of the Czech Rep.	2000-2002
University researchers	per 100,000 people	Institute for Information on Education	2002
Business R&D employees	per 100,000 people	Czech Statistical Office	2000-2002
Innovation parks	per 100,000 people	Association of Innovative Entrepreneurship	2002
Adult population with university education	(% of age 15+	Czech Statistical Office	2001
Households with internet access	% of total	Czech Statistical Office	2001
Acquired intangible fixed assets	CZK per capita	Czech Statistical Office	2000-2002
Economic crimes	per 100,000 people	Police of the Czech Rep.	2000-2002
SO ₂ emissions	tons per km ²	Czech Statistical Office	2000-2002
New housing prices	1 m ² in CZK	Czech Statistical Office	2000-2002
Population density	per km ²	Czech Statistical Office	1900