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Entrepreneurial ecosystems, entrepreneurial activity and economic growth: new evidence from European regions

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ABSTRACT
A latent class model is applied to allow entrepreneurial ecosystems (EEs) to influence the effect of entrepreneurial activity on growth in European Union regions. Using this methodology, clusters of regions that differ significantly in their relationship between entrepreneurial activity and growth are identified. This is consistent with the hypothesis that EEs affect this relationship. Subsequently, cluster membership is related to regional characteristics representing a range of components of EEs and marked differences in a variety of these regional characteristics are found. Taken together, the results support the notion that EEs help shape the impact of entrepreneurial activity on growth.

KEYWORDS
regional economic growth; entrepreneurship; entrepreneurial ecosystems; latent class analysis

JEL L26, O47, R11
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INTRODUCTION

The emerging literature on entrepreneurial ecosystems (EEs) argues that the relationship between entrepreneurship and economic performance is embedded in a (regional) EE (e.g., Malecki, 2018; Spigel, 2017; Stam, 2015) that shapes that relationship. Stam (2015, p. 1765) defines the concept of the EE as 'a set of interdependent actors and factors coordinated in such a way that they enable productive entrepreneurship'. If 'productive entrepreneurship' is understood as entrepreneurial activity in a high-quality EE that enables a positive contribution to economic growth, this implies that levels and types of entrepreneurial activity and their relationship with economic growth should vary systematically across different EEs. In high-quality EEs, we should then observe more and more productive entrepreneurship, whereas in low-quality EEs, the opposite would be true. As there is little theoretical guidance on what 'actors and factors' constitute a high-quality EE, we risk estimating tautologies when we define the EE as productive.[1] Regional policy-makers have already embraced the EE concept and there is an increased number of case studies on (primarily) successful EEs (e.g., O'Connor, Stam, Sussan, & Audretsch, 2018), but we can only learn about what constitutes a high-quality EE when we compare them with less successful ones. To date, however, there is limited evidence on the extent and conditions under which EEs actually promote 'productive entrepreneurship' and are conducive to economic performance. In this paper we provide such evidence by conducting an empirical analysis that tests for and classifies the heterogeneity across EEs and reveals how, across different ecosystems, the impact of entrepreneurial activity on growth differs.

The contribution of this paper to the literature is twofold. First, we embed the key concepts of (types of) entrepreneurial activity, (types of) EEs and economic growth at the regional level in a formal model, contributing to the emerging theory of EEs. This model complements the approach proposed by Bruns, Bosma, Sanders, and Schramm (2017), in which the authors set up a latent class model that relates entrepreneurial activity to economic growth. Compared with Bruns et al. (2017), however, we use more recent and more disaggregated data and our

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analysis covers a wider set of countries. Furthermore, when we estimate the model with appropriate contemporaneous entrepreneurial activity data, we obtain results that Bruns et al. were unable to identify. Specifically, we find a stable clustering into four ecosystem types, which we interpret as evidence that a limited number of EEs coexist, generating different growth impacts of entrepreneurial activity across regions.

Linking our empirical findings to policy allows us to make another contribution to the literature. We relate the distinct ecosystems in the clusters of regions to indicators that the emerging literature on EEs has suggested as important. We find that the clusters of regions indeed differ significantly on several elements of regional EEs, suggesting that ecosystems can be the subject of policy interventions that enhance the level and growth impact of entrepreneurial activity. We also find differences between the clusters in terms of which ecosystem elements are most important. This implies that a one-size-fit-all approach to improving the EE is destined to fail and a careful analysis of the ecosystem in place is needed before effective policies can be implemented.

The paper is structured as follows. The next section provides the theoretical background, places the study in the literature and develops the hypotheses. The third section discusses the data and explains the empirical strategy. The fourth section presents the main findings from the analysis. The fifth section summarizes and discusses policy implications.

LITERATURE REVIEW, MODEL AND HYPOTHESES

While there is a clear acceptance of the notion that entrepreneurial activity is important for economic performance, there is still no consensus on the exact underlying relations. Local contexts are seen as important, but relatively little is known about how and to what extent the link between entrepreneurship and growth may be contingent on local contexts (e.g., Bjørnskov & Foss, 2016). This has clear policy implications: What should governments do when there is something more going on than 'just' the relationship between entrepreneurial activity and growth? How and to what extent should policy-makers appreciate and possibly strengthen the existing local context, firmly rooted in institutional heritages? The emerging EEs literature holds a promise in mapping these relationships. However, before elaborating on this literature, it is useful to revisit some key theoretical underpinnings on the relationship between entrepreneurship and growth.

The theoretical basis for the hypothesis that entrepreneurship drives economic growth can be traced back to Schumpeter (1911). In his 'model' of capitalist dynamics, entrepreneurship is the activity that turns inventions into innovations and commercializes knowledge. Moreover, although without new knowledge creation there can be no growth in the Schumpeter model, he proposed that it is the process of commercialization that is the bottleneck in innovation processes. Neoclassical and later endogenous growth models ignored this important point and focused on the rate of knowledge creation as the source of economic growth. In neoclassical growth models, innovation is exogenous and endogenous growth models combine monopolistic competition with positive externalities in knowledge generation to explain how the desire for profit motivates knowledge creation (Aghion & Howitt, 1990; Romer, 1986). The knowledge spillover theory of entrepreneurship brought the *commercialization* of this knowledge back as the bottleneck in innovation and growth (e.g., Acs & Sanders, 2013; Michelacci, 2003).

Based on the academic insights of Schumpeter, a large body of empirical literature has estimated the relationship between growth and entrepreneurial activity. Researchers quickly abandoned rough proxies such as self-employment and new firm formation in favour of more precisely defined entrepreneurial activity measures provided by the Global Entrepreneurship Monitor (GEM) (Reynolds et al., 2005). The broadest proxy for entrepreneurial activity that this survey provides is total early-stage entrepreneurial activity (TEA), which classifies as entrepreneur anyone who is involved in starting up or owning and managing a business that exists up to 42 months.

Recent studies that relate this measure to growth in income and/or productivity levels tend to find positive effects. For instance, Urbano and Aparicio (2016) construct a panel of 43 countries covering the period from 2002 to 2012 and find that TEA has a positive effect on gross domestic product (GDP). But given the short time dimension, reverse causality remains an issue. In addition, findings on the effect on GDP per capita growth are much less clear (e.g., Hessels & van Stel, 2011; Prieger, Bampoky, Blanco, & Liu, 2016). Still a strong conviction remains that entrepreneurship is an important driver of economic growth (Bjørnskov & Foss, 2016; Block, Fisch, & van Praag, 2017; van Praag & Versloot, 2007) and authors have tested many proxies for entrepreneurship and alternative definitions of growth. Several studies indeed report positive effects of new firm formation on employment growth or productivity growth (Acs & Armington, 2004; Audretsch & Fritsch, 2002; Bosma, Stam, & Schutjens, 2011; Carree & Thurik, 2008). However, the evidence is far from overwhelming, especially when broader definitions of entrepreneurial activity have been applied. The relationships between 'innovative', 'ambitious' and 'growth-oriented' entrepreneurship and economic growth are stronger and more robust than between self-employment or GEM's TEA and growth, but these results risk becoming a tautology. As more exclusive and precise measures of entrepreneurship are devised, almost by definition do these measures correlate positively with the outcome one tries to estimate.

The same risk can also be found when we have a closer look at the above definition of an EE by Stam (2015, p. 1765). By defining the ecosystem as 'enabling productive entrepreneurship', the hypothesis that an EE positively affects growth through entrepreneurial activity simply cannot be falsified empirically. Although becoming increasingly popular as a concept among academics and policy-makers (Feld, 2012; Isenberg, 2010; Stam & Spigel, 2016), we agree with Stam (2015) that approaches that focus on EEs suffer from being undertheorized and the little theory we have has not yet been adequately tested. With this in mind, we propose and discuss a simple theoretical model that helps us to derive our hypotheses.

Suppose the EE in a region is characterized by an $X \times 1$ vector of characteristics. The EE drives the levels and mix of entrepreneurial activity in the region. Assuming Y types of entrepreneurial activity, this X-dimensional vector of characteristics thus maps into a $Y \times 1$ vector of entrepreneurial activities. However, by the definition of the ecosystem, it also moderates the impact of these activities on overall growth. This model can be illustrated systematically, as in Figure 1.

Most empirical studies to date focus on identifying the effects of the ecosystem on the level and types of entrepreneurial activity (the arrow in the lower left of Figure 1). Mason and Brown (2014) find that EEs play a role in the degree that regions are characterized by the creation of high growth new firms, while Audretsch and Belitski (2017) show that several components of EEs foster the start-up rate of new firms in European Union (EU) cities. By examining data from the GEM, Hechavarria and Ingram (2018) find corroborating evidence that elements of EEs are positively associated with rates of both female and male entrepreneurial activity.

More conceptual work has zoomed in on building a taxonomy of elements that characterize an EE and have distinguished systemic conditions – networks, leadership, finance, talent, knowledge, and intermediate services – and framework conditions – formal and informal institutions, physical infrastructure, and demand (Stam, 2015). A significant body of empirical work has now identified these systemic and framework conditions as factors that can be linked to entrepreneurial activity and regional growth. We briefly discuss this literature in the supplemental data online.

A taxonomy is useful in structuring our thinking about the EE and its elements and the evidence that suggests that these elements operate through as well as in addition to entrepreneurial activity on economic development. In this paper, we focus on the indirect link (arrows in the middle and top of Figure 1) from ecosystem elements to growth. More formally, we may write the growth in the gross regional product (GRP) as a function of entrepreneurial activity (which in turn is a function of the ecosystem characteristics) and the ecosystem characteristics themselves. Then we have:

$$\boldsymbol{GRP} = \boldsymbol{F}(\boldsymbol{E}^Y(\boldsymbol{EE}^X), \boldsymbol{EE}^X) \tag{1}$$

where it should be clear that the potentially complicated interactions and complementarities in the EE are 'captured' or represented in this general model by the specification of the unknown functions $\boldsymbol{F}(.)$ and $\boldsymbol{E}^Y(.)$. In an attempt to estimate the parameters of the $\boldsymbol{F}(.)$ function, some studies examine the effect of a national or regional entrepreneurship development index on productivity and growth (Acs & Szerb, 2009; Acs, Estrin, Mickiewicz, & Szerb, 2018). These composite indices combine a variety of factors related to entrepreneurial characteristics and regional inputs and the papers report significant positive effects on productivity and growth. However, the algorithm to build the index is deterministic and therefore assumes, rather than estimates, the complex interaction among the different elements of the ecosystem. The alternative approach of using simultaneous systems of equations, where the effect of (some) institutions on growth is mediated by entrepreneurial activity (e.g., Aparicio, Urbano, & Audretsch, 2016) also assumes the functional form and therefore imposes a structure on the model that has no empirical or theoretical basis.

Since we can observe and control for the level of different types of entrepreneurial activity $\boldsymbol{E}^Y$ ($\boldsymbol{EE}^X$) but cannot observe $\boldsymbol{EE}^X$ (as we do not know what dimensions of institutional framework to include and how to relate these dimensions to each other) or $\boldsymbol{F}(.)$ and $\boldsymbol{E}^Y(.)$, we argue one can only infer the existence of an EE and start testing for its most relevant dimensions by estimating the link between entrepreneurial activity and regional growth with a latent class model, allowing the data to identify classes of regions that exhibit a similar relationship between measured and observed entrepreneurial activity and measured and observed growth. Formally we use the fact that under the assumption that equation (1) is the true model, we have:

$$\frac{d\mathrm{GRP}}{dE^Y}\frac{E^Y}{\mathrm{GRP}} = \frac{d\mathrm{GRP}}{\mathrm{d}F(.)}\frac{\mathrm{d}F(.)}{dE^Y}\frac{E^Y}{\mathrm{GRP}} \tag{2}$$

where the elasticity of GRP with respect to local entrepreneurial activity of type Y, $\boldsymbol{E}^Y$, is conditioned by the vector $\boldsymbol{EE}^X$ through $\boldsymbol{F}(.)$ in the same way for all regions that share a similar vector $\boldsymbol{EE}^X$. If the true model is the model in Figure 1 and equation (1), and we assume that

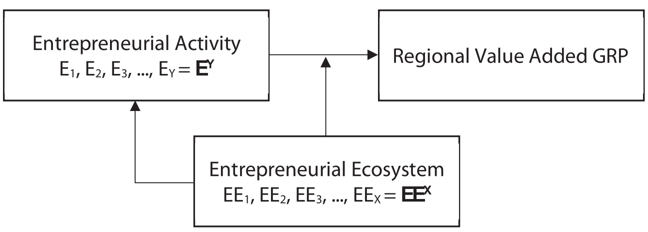

Figure 1. Simple model of the entrepreneurial ecosystem (EE).

differences in the ecosystem characteristics X drive differences in the level and impact of entrepreneurial activity of type Y, then we can also derive the hypothesis that such differences will cause the same levels of entrepreneurial activity to have a different effect on regional growth. Consequently, the EE approach predicts that we should find multiple classes for all types of entrepreneurial activity and it predicts that these classes should include roughly the same regions across our latent class regressions.

Our simple and general model thus yields three testable hypotheses. First, if EEs differ across regions, we should find multiple classes in a latent class estimation of the link between entrepreneurial activity of type Y and growth at the regional level. Second, this clustering should be more or less stable across the Y types of entrepreneurial activity. And third, variables that have been proposed as important elements of the EE, such as the systemic and framework conditions mentioned above, should be systematically different between these clusters of regions.

DATA AND METHODOLOGY

Proxies for entrepreneurial activity

To capture regional entrepreneurship, we use regional level proxies for entrepreneurial activity provided by the GEM. We aggregate annual individual level survey data for 169 regions in 25 countries in Europe. For most countries, we are able to calculate reliable indicators at the NUTS-2 level; for five countries, we can only calculate the indicators at the NUTS-1 level.

The GEM survey data are collected annually from a nationally representative sample of the working age population. In the GEM a person is classified as entrepreneur when he or she is engaged in any activity to start a business or has been running a new business that exists less than 42 months at the time of being interviewed.[2] As the annual survey waves are representative at the national but not at the regional level, we pooled the individual data for the years 2006–14 and calculated three proxies for average regional entrepreneurial activity for this period.[3] The most inclusive indicator is total early-stage entrepreneurial activity (TEA). The second indicator – opportunity-driven entrepreneurial activity (OPP) – is a subset of TEA and measures the share of the working age population that indicated being involved in early-stage entrepreneurial activity for reasons including taking advantage of new market opportunities or the desire to be their own boss. The third proxy for entrepreneurial activity (JOB) is the most exclusive, measured as the percentage of the working age population classified as early-stage entrepreneur that indicated to expect to be creating at least five new jobs in the next five years.[4]

Empirical strategy

Our model in the second section shows that if EEs differ across regions and moderate the impact of entrepreneurial activity, we should be able to identify different coefficients in a regression of growth on different types of entrepreneurial activity. To test this prediction, we follow the empirical approach proposed by Bruns et al. (2017) that consists of three steps. In the first step we estimate a standard neoclassical growth model. In the second step we use the residuals of that regression in a latent class regression model to see whether there are latent groups of regions that differ in their relationship between entrepreneurial activity and (residual) growth.[5] In the third step, we compare these groups of regions according to a set of characteristics that the literature has proposed as elements of or closely related to the quality of EEs.

Following Mankiw, Romer, and Weil (1992), we start by specifying our baseline model as:

$$\begin{aligned} g_i &= \frac{y_{it} - y_{it-1}}{T} \\ &= \beta_0 + \beta_1 y_i + \beta_2 k_i + \beta_3 h_i + \beta_4 n_i + \beta_5 P_i \\ &\quad + \beta_6 R_i + \beta_7 U_i + \epsilon_i \end{aligned} \tag{3}$$

where i denotes regions; g_i is the average annual growth rate of GRP per capita for the period 2006–14; y_i is the natural logarithm of GRP per capita at the start of the period; k_i and h_i are the shares of income invested in physical and human capital; and n_i is the average population growth rate. The investment rate for physical capital is measured by the average of gross fixed capital formation divided by GRP for the period 2006–14. We use tertiary education to capture human capital investment by taking the share of the working-age population aged 20–24 years, multiplied by tertiary education participation among the population aged 20–24. To control for population growth, n_i, we include the average annual rate of population growth for 2006–14.

Next, we add control variables to capture growth variation related to economic geography. We include population density P_i, measured as total population divided by the squared kilometres of the region to control for agglomeration economies (Puga, 2002). We also include controls for related variety R_i and unrelated variety U_i, as recent studies find that the industrial composition of an economy impacts growth (Content & Frenken, 2016). We calculate unrelated variety as the entropy among the employment shares in two-digit industries and related variety as the weighted sum of entropies among four-digit employment shares within two-digit industries (Frenken, Van Oort, & Verburg, 2007) (Table 1).

The specification in equation (3) does not take into account productivity differences between countries and regions. When between-country differences are not considered, distinct marginal effects of the factors of production between countries are not observed and therefore end up in the error-term. The resulting bias that may arise can be minimized by estimating equation (3) with country-specific fixed effects using a multilevel model, specified as:

$$\begin{aligned} g_{ij} &= \beta_0 + \beta_1 y_{ij} + \beta_2 k_{ij} + \beta_3 h_{ij} + \beta_4 n_{ij} + +\beta_5 P_{ij} \\ &\quad + \beta_6 R_{ij} + \beta_7 U_{ij} + \delta_j + \epsilon_{ij} \end{aligned} \tag{4}$$

Table 1. Descriptive statistics.

Variable		Source	Mean	SD	Minimum	Maximum
GRP p/c growth	g	Eurostat	0.013	0.020	−0.035	0.065
Initial GRP p/c	y	Eurostat	24,220	9310	6016	64,236
Physical capital investment rate	k	Eurostat	−0.024	0.034	−0.116	0.058
Human capital investment rate	h	Eurostat	6.490	3.352	0.593	23.858
Population growth	n	Eurostat	0.002	0.007	−0.016	0.028
Population density	P	Eurostat	4.973	1.256	1.126	8.829
Related variety	R	BvD	1.917	0.311	0.728	2.455
Unrelated variety	U	BvD	5.045	0.401	2.773	5.574
Total early-stage entrepreneurial activity	E^{TEA}	GEM	6.354	2.003	2.521	14.358
Opportunity entrepreneurial activity	E^{OPP}	GEM	4.689	1.476	1.608	10.241
Job growth expecting entrepreneurial activity	E^{JOB}	GEM	1.527	0.940	0.000	5.116

Note: Except for initial gross regional product (GRP) per capita (p/c), all variables are measured as averages over the period 2006–14. BvD, Bureau van Dijk.

where i denotes regions, j denotes countries and the dummy variables δ_j allow for country-specific intercepts.

To estimate the cross-sectional growth impact of entrepreneurial activity, one can simply add indicators of entrepreneurial activity directly into the model (e.g., Acs et al., 2018). Putting the factors of production as well as the additional regional variables in vector 'X_i to shorten the notation, this would amount to estimating:

$$g_i = \beta_0 + \beta_1 E_i + \beta' X_i + \epsilon_i \quad (5)$$

$$g_{ij} = \beta_0 + \beta_1 E_{ij} + \beta' X_{ij} + \partial_j + \epsilon_{ij} \quad (6)$$

where E_i represents the indicator of regional entrepreneurial activity. One can also try to identify the effect of EEs on regional growth as in Szerb, Lafuente, Horvath, and Pager (2018) and estimate equations (5) or (6) with an index capturing the quality of the EE in a single number. Szerb et al. (2018) regress regional value-added and employment growth on a set of explanatory variables, including interaction variables between a region's REDI score and two indicators of regional entrepreneurship. However, that approach assumes that the regional entrepreneurship and development index (REDI) score is an accurate and complete indicator of a region's EE. That assumption is problematic given that there is little agreement on what EEs contain and how the various elements interact. Furthermore, such an approach also assumes that all regions share the same configuration of the ecosystem and only regional differences in the underlying variables can explain changing impacts of entrepreneurial activity.

In our case, the disadvantage of estimating equations (5) or (6) for the whole sample of regions is that a single β_1 is estimated across all regions. Consequently, the relationship between entrepreneurial activity and growth is assumed to be the same across all regions in the sample by construction. As we have argued above, however, differences in EEs are likely to cause regional heterogeneity in the relationship between entrepreneurial activity and growth. The implication of this for equations (5) and (6) is that regional variation in the quality of the ecosystem that causes variation in the degree to which entrepreneurial activity impacts upon growth ends up in the error term. As the error term is therefore no longer random, this introduces a bias in the estimations.

One approach to deal with this is to group regions according to factors that influence growth patterns and estimate separate regressions, thereby allowing the effect of entrepreneurial activity to differ between the groups.[6] However, such an approach relies on the use of arbitrary cut-off points and allows the effect to only vary between predefined groups. Moreover, given the multidimensionality of EEs, the separation of regions based on individual components of EEs is likely to produce relatively uninformative results.[7]

Therefore, in this paper we follow Bruns et al. (2017) who use latent class regressions to allow for the EE to influence the size and signature of the relationship that we estimate between entrepreneurial activity and growth. With this approach, regions are endogenously sorted into unobserved latent groups, without the need to make a priori assumptions about what may distinguish different groups of regions. To conduct this latent class regression, we take the residuals from the estimation of equation (4) and regress them on our indicators of entrepreneurial activity using:

$$\epsilon_{i|k} = \alpha_{0|k} + \alpha_1 E_{i|k} + \varepsilon_{i|k} \quad (7)$$

where $k = 1, \ldots, K$ denotes the classes; and K indicates the optimal number of classes. This can be rewritten into a latent class regression model (DeSarbo & Cron, 1988; Leisch, 2004), given by:

$$f(\epsilon|E, \theta) = \sum_{k=1}^{K} \pi_k f_k(\epsilon|E, \theta_k) \quad (8)$$

$$\pi_k > 0, \quad \sum_{k=1}^{K} \pi_k = 1$$

where ε is the dependent variable, representing the residuals from equation (4), estimated without E; E is the independent variable capturing entrepreneurial activity; and π_k is the unconditional probability of a region

Table 2. Ordinary least squares (OLS) and multilevel growth regressions.

	OLS					Multilevel		
GRP p/c growth	**(1)**	**(2)**	**(3a)**	**(3b)**	**(3c)**	**(4a)**	**(4b)**	**(4c)**
Initial GRP p/c	−0.019**	−0.021**	−0.017**	−0.020**	−0.009**	0.001	0.001	0.0004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Physical capital	0.388**	0.293**	0.298**	0.293**	0.271**	0.073**	0.073**	0.074**
	(0.029)	(0.031)	(0.029)	(0.029)	(0.025)	(0.027)	(0.027)	(0.027)
Human capital	0.001	−0.001	−0.003*	−0.003	−0.005**	−0.001	−0.001	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Population growth	−0.544**	−0.657**	−0.715**	−0.710**	−0.810**	−0.494**	−0.527**	−0.552**
	(0.191)	(0.176)	(0.164)	(0.166)	(0.146)	(0.138)	(0.139)	(0.136)
Population density		0.003**	0.003**	0.003**	0.002**	0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Related variety		−0.003	−0.001	−0.002	0.001	−0.002	−0.002	−0.002
		(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Unrelated variety		0.014**	0.014**	0.014**	0.009**	0.005*	0.005*	0.005*
		(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
$\text{Eship}^{\text{TEA}}$			0.224**			−0.016		
			(0.044)			(0.044)		
$\text{Eship}^{\text{OPP}}$				0.264**			0.025	
				(0.057)			(0.051)	
$\text{Eship}^{\text{JOB}}$					0.831**			0.187
					(0.094)			(0.114)
RE constant						0.0169	0.0163	0.0148
RE residual						0.0053	0.0053	0.0054
Constant	0.214**	0.149**	0.097**	0.132**	0.048^{+}	−0.016	−0.013	−0.008
	(0.031)	(0.032)	(0.031)	(0.030)	(0.028)	(0.024)	(0.024)	(0.024)
R^2/BIC	0.629	0.707	0.748	0.742	0.803	−1065.6	−1066.1	−1069.5

Notes: Standard errors are shown in parentheses ($^{+}p < 0.1$; $*p < 0.05$; $**p < 0.01$).
Models 1–3 are OLS regressions omitting country fixed effects. Models 4 are multilevel regressions including country random effects. For models 1–3, R^2 is shown; for models 4, the Bayesian information criterion (BIC) is reported.

belonging to cluster k. The unconditional probabilities are larger than 0 and add up to 1, and $\theta = (\pi_1, \ldots, \pi_k, \theta_1, \ldots, \theta_k)$ is the vector of all parameters (in our case a slope coefficient and a constant). Each density function f_k has its own cluster-specific parameters θ_k. To put it more intuitively, we allow the model to estimate a different constant and slope coefficient in each class and make the sorting into classes an endogenous part of the estimation. We describe this methodology in more detail in the supplemental data online.

RESULTS

To obtain a baseline we estimate our model on the whole sample of 169 regions, as shown in Table 2. In model 1, representing the standard Mankiw et al. (1992) specification, we find a negative and significant coefficient for the initial level of GRP per capita, indicating the presence of conditional growth convergence among European regions. Investment in physical capital is positively associated with growth. The insignificant coefficient on human capital investment is perhaps surprising, but in the regional EU context it could be explained by limited variation in enrolment and/or high mobility of tertiary-educated individuals. The rate of population growth is negatively associated with growth in GRP per capita, but its elasticity is less than one, suggesting positive but decreasing returns to labour at the regional level.

In model 2, we augment the standard Mankiw et al. (1992) specification by adding the economic geography variables to the growth regression. The estimated effect of population density is positive, suggesting the presence of agglomeration advantages. In line with Frenken et al. (2007), who hypothesize that unrelated variety may act as a hedge against economic shocks, we also find that regions with higher rates of unrelated variety seem to have outperformed the others in the crisis and recovery period of 2006–14. In contrast, related variety does not have a significant impact on a regions' growth rate.

Models 3a–c add the indicators of regional entrepreneurial activity. The estimated positive effect becomes larger and more precise when moving from generic to more narrowly defined types of entrepreneurial activity. In particular, the estimated growth effect of JOB is statistically significantly larger than the effect of TEA and OPP. These findings, however, should be interpreted with care.

As the estimated models do not control for country specific effects, the estimated coefficients might be biased due to systematic country level variation not explicitly modelled in these estimations.

To clean out such biases, we re-estimate models 3a–c, adding country random effects.[8] Models 4a–c show that the result of this is that the precision of the estimated effects is lowered and, although the signs are the same, the size of the estimated coefficients changes quite significantly for capital investment and population growth. This suggests that investment rates and population growth correlate more between regions within a country then across countries, as one might also expect. The results also show that the estimated effect of the three types of entrepreneurial activity decreases in size and turn insignificant, although the effect of JOB is just insignificant at 10%. Again, this indicates that between-country variation is important for explaining regional differences. After taking out the between-country variation, too little within-country variation remains to identify the effect of entrepreneurial activity at the regional level.

The models presented in Table 2 assume a single coefficient for entrepreneurial activity across all regions and do not allow for the possible presence of heterogeneity of the growth impact of entrepreneurial activity across groups of regions with a similar EE. To assess whether the full sample of regions can be classified into distinct groups of regions, we turn to a latent class analysis. We take the residuals from equation (4) excluding entrepreneurial activity and regress these on the different indicators of entrepreneurial activity using a latent class model.

We first determine whether a configuration with more than one cluster is indeed preferred, as that would indicate that some groups of regions are distinct in their relationship between entrepreneurial activity and growth. We find that for TEA and OPP, the highest BIC values are obtained in a five- and four-cluster configuration, respectively. In contrast, in the case of JOB the results indicate that the best model fit is achieved when only one cluster is used. The supplemental data online provides a clear overview of the different model fits with one–seven clusters. Overall, JOB thus contributes equally to residual regional growth across all regions in our sample.[9] We therefore focus the remainder of our analysis on TEA and OPP. In order to avoid overfitting the data, we estimate the model with the restriction that the minimal prior weights are > 0.05 (approximately 10 regions). In the case of TEA, this means that one cluster is removed during the estimation process.

In contrast to Bruns et al. (2017), the present findings thus suggest that a configuration with more than one cluster is to be preferred. Our findings therefore fundamentally differ with Bruns et al. and clearly show that the estimated growth effect of entrepreneurial activity does differ between groups of regions. We believe that these new results are due to the fact that we have more recent data and for more regions in a wider variety of countries. Bruns et al. confine their analysis to estimating the impact of average entrepreneurial activity for 2001–06 (before the crisis) on residual growth in 2007–14 (in the crisis). Our use of more recent indicators of entrepreneurial activity and the larger number of regions in the sample can explain why we identify the clusters that Bruns et al. only hypothesize to exist. These results indicate, to our knowledge for the first time, that the relationship between entrepreneurial activity and growth is not uniform across endogenously clustered regions in the EU.

The results of the latent class regressions with TEA and OPP as explanatory variables are shown in Table 3 and Figure 2. The dependent variable in these regressions is the residual obtained from the multilevel growth regression excluding entrepreneurial activity (equation 4). In the case TEA, the regions get endogenously sorted into one large group 1 of 101 regions, characterized by an insignificant constant and a significant and positive slope coefficient. Next is a medium sized group 2 of 38 regions that has a large negative and significant slope coefficient, whereas the constant is positive and significant. Group 3 with 16 regions has a moderately negative and significant slope coefficient and a relatively high constant, whereas the smallest cluster, group 4 with 14 regions, has a positive significant constant and slope coefficient. Group 1 covers regions in Scandinavia and West and Central Europe. Group 2 mostly consists of regions in Southern Europe, Ireland, and some regions in north Germany. Group 3 contains Eastern European regions. Group 4 contains some southern regions of Germany and some regions in Slovakia, Austria and Hungary.

The scatterplot in Figure 2(b) corresponds to the regression results in Table 3, where we clearly observe the cluster of regions in Eastern member states (group 3) that recovered quickly from the crisis, more or less independent of TEA, whereas sluggish growth persisted in Ireland and big parts of Spain and Greece (group 2) and the effect of TEA was in fact strongly negative. Note in the scatterplot that the small cluster of observations with high growth and low TEA consists of north and eastern German regions. These regions may have been sorted into this cluster because formal employment adds more to growth in these regions, but the reason may also be more mundane as these regions just happen to lie more or less on the regression line that fits the other regions in the cluster best.

The second part of Table 3 depicts the regression results when we use OPP as our indicator for entrepreneurial activity. Again, we see one big Group of 130 regions and three smaller groups with 15, 13 and 11 regions respectively. Group 1 has a positive slope coefficient and insignificant intercept and contains regions spread over Scandinavia, Western Central and Southern Europe, with the exception of Greece. Group 2, with an insignificant slope coefficient and high positive constant contains regions located in Eastern European countries. Group 3 shows a strong negative slope coefficient and positive constant and includes regions mostly from eastern and southern Germany, whereas group 4 contains only regions in Greece, characterized by negative growth. In groups 2 and 4 we do not observe a significant association of OPP with the growth residual, whereas in groups 1 and 3 we observe a positive and negative association, respectively.

Table 3. Latent class regressions with total early-stage entrepreneurial activity (TEA) and opportunity-driven entrepreneurial activity (OPP).

	TEA 1	TEA 2	TEA 3	TEA 4
E^{TEA}	0.222 (0.051)**	−0.719 (0.112)**	−0.161 (0.026)**	0.265 (0.007)**
Constant	−0.001 (0.003)	0.04 (0.007)**	0.066 (0.002)**	0.009 (0.000)**
Prior	0.527	0.317	0.092	0.064
Size	101	38	16	14
	OPP 1	**OPP 2**	**OPP 3**	**OPP 4**
E^{OPP}	0.329 (0.078)**	−0.113 (0.055)	−0.505 (0.052)**	0.085 (0.063)
Constant	−0.005 (0.004)	0.058 (0.003)**	0.036 (0.002)**	−0.031 (0.003)**
Prior	0.6743	0.0883	0.1746	0.0629
Size	130	15	13	11

Notes: Standard errors are shown in parentheses ($^{+}p < 0.1$; $*p < 0.05$; $**p < 0.01$).
Dependent variable: Residual model (2). With E^{TEA} as a proxy for entrepreneurial activity, we obtain a log-likelihood of 477.71 (d.f. = 15) and a Bayesian information criterion (BIC) of −878.47. With E^{OPP} as a proxy for entrepreneurial activity, we obtain a log-likelihood of 465.14 (d.f. = 15) and a BIC of −853.34.

Note also that the positive slope coefficient in the large group 1 is larger when OPP is used as a proxy for entrepreneurial activity, suggesting that OPP captures growth enhancing entrepreneurship better than TEA does.

Table 3 and the scatterplot in Figure 2(d) reveal that regions in groups 2 and 4 seem to be clustered together primarily because of a high and low average level of residual growth, respectively. The latter is undoubtedly related to

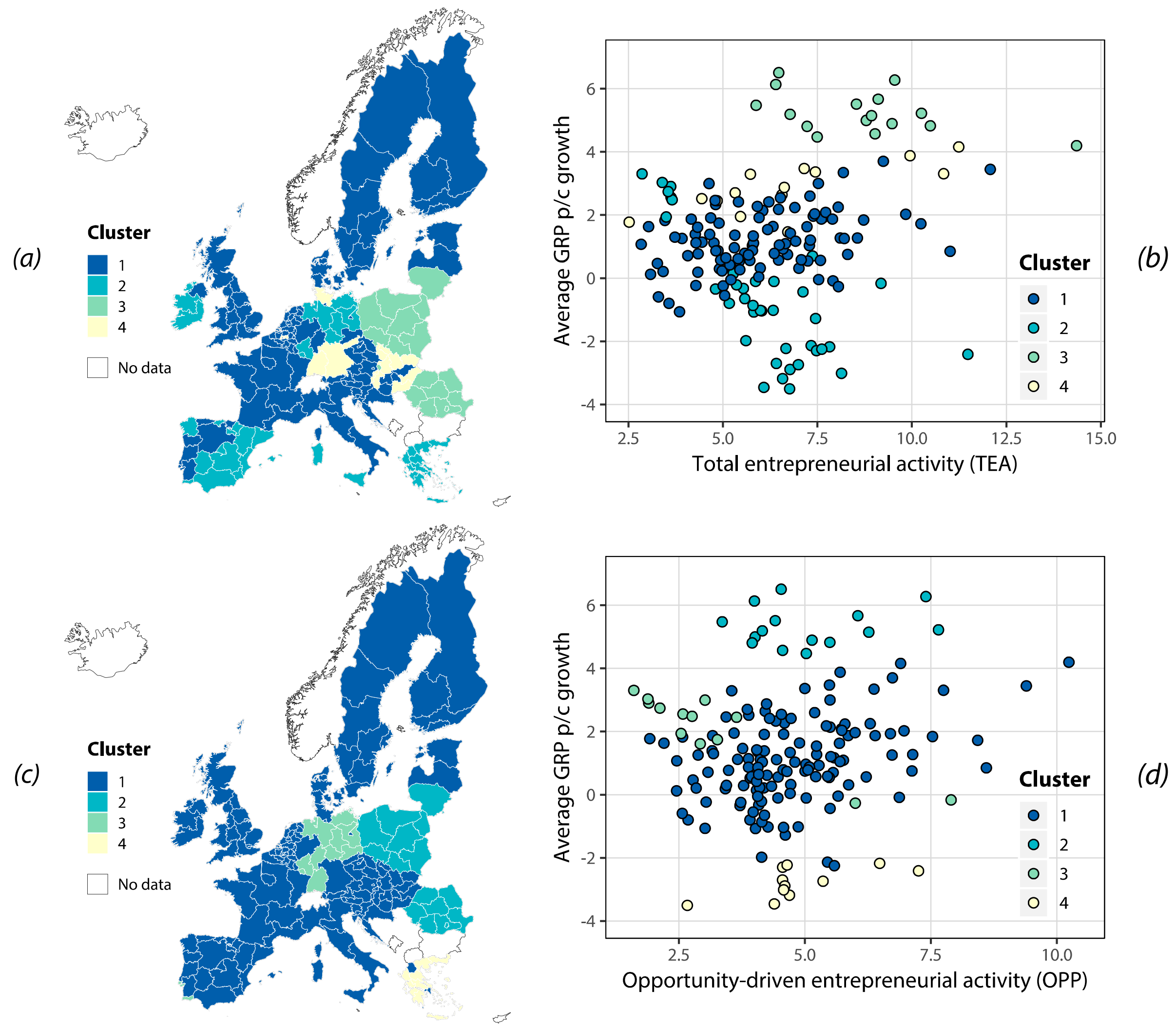

Figure 2. Maps (a, c) and scatterplots (b, d) of latent class clusters for total entrepreneurial activity (a, b) and opportunity-driven entrepreneurial activity (b, c).

the fact that Greece has been in a severe recession and experienced a slow recovery due to macroeconomic instability in the period under study, whereas for Eastern European regions in group 2 the impact of the recession was milder and/or the recovery was not driven by entrepreneurial activity. For group 1 there is a significant positive effect of OPP, whereas for the German regions in group 2 this relationship seems less pronounced, given that residual growth is high in the East, where also OPP is lowest. Tentatively, one might conclude that the German EE is less effective in turning even opportunity-driven entrepreneurial activity into growth and/or that other engines of growth are more important, especially in the former East German *Länder* (e.g., Sanders et al., 2018).

Overall, the findings from the latent class regressions clearly suggest that the relationship between entrepreneurial activity and regional growth is not uniform across regions. This leads to the question whether this regional heterogeneity is related to the underlying EEs in the clusters of regions. To examine this, we compare cluster means for a selection of regional characteristics that have been proposed as direct components of or are closely related variables to regional ecosystems. We are guided in our choice of variables by other studies that have analysed various components of EEs (Audretsch & Belitski, 2017; Auerswald & Dani, 2017; Bell-Masterson & Stangler, 2015; Spigel, 2017; Stam, 2018; Stam & Spigel, 2016) and should be seen as an explorative exercise.

Table 4 presents cluster means together with *t*-statistics that indicate whether the means are significantly different between pairs of clusters. As we want to examine whether elements of the EEs explain differences between clusters with a positive growth impact or no positive growth impact from entrepreneurial activity, we group together clusters for which we find a positive effect and clusters for which we find a negative or insignificant

Table 4. Cluster means comparison and *t*-tests.

	Total early-stage entrepreneurial activity (TEA)			Opportunity-driven entrepreneurial activity (OPP)		
	Cluster mean			Cluster mean		
	1 (1 + 4)	2 (2 + 3)	*t*-statistic	1	2 (2 + 3 + 4)	*t*-statistic
Formal institutions						
Corruption	0.43	−0.57	6.78**	0.31	−0.51	4.74**
Quality of government	0.45	−0.66	8.16**	0.34	−0.70	6.55**
Impartiality	0.43	−0.58	7.40**	0.32	−0.56	5.49**
Entrepreneurship culture						
Entrepreneurship is a good career choice	0.58	0.62	−2.93**	0.58	0.62	−1.77+
Successful entrepreneurs have status	0.68	0.67	0.75	0.67	0.69	−1.53
Fear of failure	0.41	0.53	−11.20**	0.42	0.54	−9.04**
Physical infrastructure						
Household access to internet	84.08	72.84	7.65**	82.69	73.14	5.50**
Accessibility of motorways	97.01	42.23	4.91**	87.19	53.88	2.57*
Accessibility of railways	92.94	50.45	4.75**	85.29	59.58	2.48*
Accessibility of passenger flights	1059.6	271.1	3.00**	909.4	468.5	1.48
Demand						
GRP p/c	26,160	20,088	4.45**	25,981	18,349	5.58**
Population density	461.7	260.2	2.31*	455.3	203.9	1.31
Networks						
SMEs with innovation cooperation	0.43	0.22	7.73**	0.40	0.23	5.32**
Know someone that started a firm	0.33	0.32	0.28	0.33	0.31	1.29
Talent						
Human capital	6.21	7.10	−1.31	6.30	7.11	−0.95
Creative class employment	9.34	6.84	6.18**	9.03	6.89	4.58**
Knowledge workers	41.28	31.26	8.01**	39.94	31.88	5.36**
New knowledge						
R&D ratio	1.85	0.88	4.78**	1.65	1.17	2.03*
Patent applications/mil. inhabitants	196.07	46.54	3.26**	156.70	126.16	0.58

Note: GRP, gross regional product; p/c, per capita; R&D, research and development; SMEs, small and medium-sized enterprises.

effect. This means that in the case of TEA, we group together clusters 1 and 4 and clusters 2 and 3. In the case of OPP we compare cluster 1 with clusters 2–4. We provide a comprehensive overview of cluster means and *t*-statistics of all separate clusters for both TEA and OPP in the supplemental data online.

Starting with TEA, there are clear differences between the two groups with respect to their formal institutions. Group 1, with a positive and significant coefficient for TEA on growth, has the highest perceived freeness of corruption, quality of government and impartiality of institutions. These differences are highly significant when group 1 is compared with group 2, where regions have a negative or insignificant coefficient for TEA. Looking at cluster means when we use OPP as our indicator of entrepreneurial activity we see similar significant differences, be it that group 1 scores slightly lower on the three formal institutions variables. Next, although group 1 and group 2 differ less on indicators capturing entrepreneurial culture, we do find significant differences. Perhaps surprisingly, for both TEA and OPP, group 2 scores significantly higher on the entrepreneurial culture indicators. A possible explanation for this difference could be that in regions where a lot of people enter as entrepreneurs, the quality of these entrepreneurs and therefore their marginal contribution to growth may decrease.

The various indicators that relate to the physical infrastructure of a region are also significantly different between groups 1 and 2 for TEA and OPP, with group 1 having on average better infrastructure. Again, we find that the differences are somewhat more pronounced for TEA, suggesting that for TEA to positively affect GRP, the infrastructural components of the ecosystem are more important than for OPP. Demand, measured by GRP per capita, is significantly higher in group 1. Population density, although significantly different in the case of TEA, is not significantly different between groups 1 and 2 for OPP. The proxy for networks in the form of the share of SMEs that are cooperating in innovation activities is almost twice as large for group 1 compared with group 2. The second indicator of networks – whether people know someone who has started a business – does not significantly differ between the two groups.

We observe significantly higher levels of creative class employment and knowledge workers in group 1 compared with group 2, but interestingly human capital is not significantly different between the two groups. This is probably related to the fact that we control for the effect of human capital in the first step of our estimation procedure. The creation of new knowledge – as measured by research and development (R&D) and the number of patent applications – is also significantly higher in group 1 compared with group 2 in the case of TEA. For OPP, only the R&D ratio is significantly higher for group 1.

Overall, the findings in Table 4 indicate that regions in the group that experience a positive growth impact of entrepreneurial activity score better on a range of elements that are linked to EEs. The results also show that these differences become smaller or even turn insignificant when we use a narrower definition of entrepreneurial activity (OPP). Going back to the most restrictive definition of entrepreneurial activity, JOB, there would indeed be no differences by construction as our latent class model identified one cluster with a positive, be it insignificant coefficient for entrepreneurial activity on growth.

The findings in Table 4 only provide general indications that the groups of regions are structurally different according to their regional characteristics, and further research is necessary to identify their importance for the differential growth impact of entrepreneurial activity. Furthermore, the cluster means do not clarify how regional characteristics may interact and create systemic differences between the groups of regions. This said, we do find that the results are suggestive in that EEs are linked to the heterogeneity of the growth impact of entrepreneurial activity across the groups of regions in the sample, as the model of EEs predicts they would if ecosystems are assumed to differ across regions. The results confirm the strong intuitions of policy-makers and academics alike and replace the assumption that EEs matter with a sound basis of empirical evidence.

SUMMARY AND POLICY RECOMMENDATIONS

Entrepreneurial activity is increasingly seen as an important driver of economic growth and development. The present paper provides evidence for the EU that the relationship between entrepreneurial activity and growth systematically differs between groups of regions. Moreover, we show that these differences are related to regional characteristics that can be related to the quality of these regions' EEs.

In a standard neoclassical growth model for the full sample of regions, we find significant positive effects of our three indicators of regional entrepreneurial activity. When we include random country effects, the estimated effect of entrepreneurial activity turns insignificant. The drawback of this approach, however, is that the inclusion of country random effects masks the presence of differences in the relationship between entrepreneurial activity and growth among groups of regions that are related to characteristics of the EE in these regions.

To assess whether regions differ in their relationship between entrepreneurial activity and growth, we apply a latent class analysis which allows for an endogenous sorting of regions into groups. For both TEA and OPP we find that the sample of regions can be divided into four groups that differ markedly in their relationship between entrepreneurial activity and growth. Next to a large core group that is characterized by significant positive effects of TEA and OPP on economic growth, there are smaller groups of regions where positive effects are smaller, insignificant or even negative. Within the context of the literature that argues that EEs underlie structural relationships between entrepreneurial activity and economic outcomes, we take these findings as supporting the notion that ecosystems exercise an important influence on the growth impact of different types of entrepreneurial activity.

As an exploratory analysis, we compare the groups of regions looking at a range of regional characteristics that are components of, or closely linked to, EEs. The group of regions that is characterized by a positive impact of entrepreneurial activity on growth tends to perform well on various indicators of formal and informal institutions. It also outperforms the other group of regions when looking at physical infrastructure, networks, talent and the creation of new knowledge.

These tentative results give indications on how the literature might proceed in developing a richer understanding of EEs. Our parsimonious and generic model provides clear and testable hypotheses and the results suggest that indeed the EE matters and matters differently in different regions. Moreover, the results also shed light on the debate on the appropriate proxy for entrepreneurial activity. In the context of EEs, it makes little sense to define entrepreneurial activity exclusively as those activities that contribute directly to growth. This paper has shown that a more fruitful way forward is to investigate how these crude and inclusive proxies of entrepreneurial activity that we have used (fail to) translate into growth at the regional level. In that way the EE is conceptualized as driving not only the level of entrepreneurial activity in a region, but also as a mediator of the effect of such activity on the economy at large.

Finally, we tentatively distil three policy recommendations from our findings. First, the current policy climate in the EU is characterized by a strong emphasis on the implementation of a uniform strategy to promote entrepreneurship. As our findings show, such policies will not necessarily lead to higher growth. Depending on the characteristics of the underlying regional EE, additional policy measures are required to allow the expected positive effects on regional growth to actually materialize. We have shown that regions in which the ecosystem functions well, several formal and informal institutional conditions are more prevalent. But these comparisons cannot be interpreted as establishing a causal link. Before drawing such conclusions, more research is necessary to establish the exact causal links in given ecosystems. In general terms it is likely that all regions benefit from improving their EE, but what constitutes an improvement in any specific region depends on its specific preconditions and requires more in-depth investigation than our data allow.

Second, we take our findings to indicate that governments need to adopt a place-based and holistic approach when examining the EE of their regional economy. In our analysis, we offer a first glance at how groups of EU regions differ on a range of elements of EEs. At a basic level, the findings from this analysis can be interpreted as indicating that governments should try to improve these indicators in order to strengthen the relationship between entrepreneurial activity and growth. However, such indicators need to be seen in the context of individual regional economies in order to understand their impact and to assess whether and how they should be improved. Furthermore, these various elements are part of a structural framework that may operate in different ways in specific regional settings. Therefore, governments need to analyse both the individual elements and the unifying framework of the EE in their regional economies in order to identify those policy areas and measures that are most urgent and important. This calls for a clever combination of further quantitative and qualitative empirical research at the level of individual regional ecosystems, as proposed, for example, in Sanders et al. (2018).

Third, our findings imply that regional governments need to adopt a more detailed cost–benefit approach when deciding on using entrepreneurial activity as a vehicle for economic growth. Governments of regions where the positive relationship between entrepreneurial activity and growth does not materialize may change this situation by improving their EE. In making the assessment whether or not this is worthwhile, such governments need to compare the costs that improving the ecosystems will entail with the benefits that the region may enjoy when entrepreneurial activity leads to higher growth. This trade-off may turn out quite differently for such diverse regions as, for example, Bavaria, Attica and Eastern Poland. The differences in the relationship between entrepreneurial activity and growth that we have identified, together with the differences in characteristics between the groups of regions, may indicate that it is economically not feasible or simply not cost effective for some regions to establish a meaningful positive growth effect from entrepreneurial activity. Of course, regions may choose to promote entrepreneurial activity for a variety of reasons, but assuming that the ultimate goal of regional governments is to foster economic growth in their region, it may be that policies to foster growth via other means than entrepreneurial activity are more appropriate.

DISCLOSURE STATEMENT

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NOTES

1. Some argue that EEs are only present in regions where productive entrepreneurship exists. In contrast, we take the view that EEs can exist in all regions, but that they differ in quality, creating performance differences.
2. See Reynolds et al. (2005) and Bosma (2013) for a detailed explanation of the methodology underlying the GEM survey.
3. For example, see Bosma and Sternberg (2014) and Content, Frenken, and Jordaan (2019), who use a similar approach to calculate indicators of regional

entrepreneurship in the EU. The limitation of using this approach is that it results in cross-sectional indicators averaged for the period, preventing us from adding a time dimension to our analysis.

4. Figure C1 in Appendix C in the supplemental data online shows the distribution of the prevalence rates of these different types of entrepreneurship and what NUTS level is used for which country.

5. By taking this two-step procedure, we implicitly impose on the model that the estimated parameters of the growth equation are equal across regions. In a sample that includes developing countries, this assumption would be too restrictive, but in a sample of European regions, this should be acceptable. Moreover, as we are primarily interested in EE, this procedure allows only the marginal effect of entrepreneurial activity to differ across latent classes.

6. Factors to distinguish between groups of regions include, for example, income (Hessels & van Stel, 2011), institutions (Hall & Gingerich, 2009) or geographical location (Redding & Venables, 2004).

7. Bosma, Content, Sanders, and Stam (2018) use a different approach by positing entrepreneurial activity as a mediator of the effect of institutions on economic growth. However, such an approach still assumes that the effect of ecosystem characteristics is the same across units and it only examines one element of the underlying EE.

8. At the 5% significance level, a Hausman specification test of ordinary least squares (OLS) versus random effects rejects OLS in favour of random effects (1327.78, d.f. = 7). A random effects specification is not rejected in favour of fixed effects specification (8.48, d.f. = 7).

9. One would expect this to happen first to the more specific measures of entrepreneurial activity, with, on the one hand, extreme entrepreneurship strictly defined as, for example, only those activities that contribute to GRP growth and, on the other, inclusive proxies that include all kinds of 'entrepreneurial' activity such as self-employment or new firm formation. As explained by Bosma et al. (2018) and also discussed above, TEA and OPP are more inclusive and noisier than JOB.

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