

The impact of knowledge complexity on total factor productivity in European metropolitan regions

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1. Introduction

Economic development is uneven among as well as within countries. In addition to differences economic development between countries - often proxied by income levels -, we also observe wide disparities in economic (mis)fortunes between subnational regions within countries. This variation is often explained by productivity differences which allow some countries (or regions) to prosper while others fall behind (Nelson and Winter, 1977; Prescott, 1998; Hall and Jones, 1999). Even though these differences in productivity are driven by a large number of characteristics of the economy (Porter, 1990; Scott and Storper, 2003; Rodríguez-Pose, 2013; Rodríguez-Pose and Di Cataldo, 2015), technological progress is generally considered as the most essential factor for productivity gains and economic growth.

While scholars of multiple fields have formulated thoughts on the role of the development and distribution of new technologies for (regional) economic growth for decades now (Schumpeter, 1939; Solow, 1956; Nelson and Winter, 1982; Romer, 1990; Glaeser *et al.*, 1992) more recent literature points to the ever increasing importance of new knowledge, also due to increased competition in times of pervasive globalisation and global value chains (see e.g. OECD, 1996; Foray, 2004). Despite the fact that knowledge production is seen as a key element to develop and sustain regional economic competitiveness, what characteristics of the region may boost innovative agents within the region and what the expected benefits of producing new knowledge are, remain much debated questions. Firms are not isolated from their environment, but embedded and inter-linked with their innovative activities in their regional surrounding, exploiting localised capabilities such as local or regional infrastructure, competing firms, institutions, endowments of resources, knowledge and skills (Storper, 1997; Maskell and Malmberg, 1999). Not only is the development of new technologies to a large degree influenced by regional characteristics, the diffusion of knowledge is also very much localised (Jaffe, Trajtenberg and Henderson, 1993), enabling firms' and regions' competitive advantage in today's international competition. However, to complement or substitute local capabilities, innovative firms have in recent decades increasingly tapped external knowledge sources (Bathelt, Malmberg and Maskell, 2004; Breschi and Lenzi, 2015; Van der Wouden and Rigby, 2019; Van der Wouden, 2020; Balland and Boschma, 2021) often in the form of specific R&D collaboration networks (Fritsch and Franke, 2004; Scherngell, 2013).

The importance of knowledge production in general notwithstanding, it is clear that not all knowledge has the same quality or value (Foray, 2004). In an economic and industrial/innovation policy sense, knowledge or technologies that are harder to be imitated and diffused in geographical space offer more sustained competitive advantage for the innovating firms and regions. In this context, the concept of knowledge complexity has been developed recently to empirically approach the elusive notion of knowledge quality (Sorenson, Rivkin and Fleming, 2006; Balland and Rigby, 2017). Knowledge is of high quality if it is tacit - that is hardly codifiable and difficult to transfer between people and places (Polanyi, 1958, 1966;

Kogut and Zander, 1992; Gertler, 2003). Kogut and Zander (1993) identify complexity as an important element of what makes knowledge tacit. Consequently, the more complex knowledge is, the more it is subject to individual learning and experiences that cannot easily be codified. As it is naturally extremely difficult or even impossible to measure tacit knowledge or the underlying capabilities that enable innovating actors to develop such knowledge, empirical operationalisations of economic or knowledge complexity typically employ indirect approaches. These either approximate complexity with the difficulty to combine the necessary components to develop a piece of knowledge or technology (Fleming and Sorenson, 2001; Broekel, 2019), or utilise the real-world spatial distribution of knowledge production to signal which types of knowledge (often proxied by patent classes) are inherently hard to produce and therefore valuable in a competitive sense (Hidalgo and Hausmann, 2009; Tacchella *et al.*, 2012; Pugliese *et al.*, 2019).

While not without critique (e.g. Martin and Sunley, 2022; Nomaler and Verspagen, 2022), numerous recent studies within Economic Geography have taken up the topic of knowledge complexity, examined the development of regional complex knowledge over time and have started to analyse its effect on the regional economy in the mid to long-term (e.g. Balland and Rigby, 2017; Pintar and Scherngell, 2022). In addition to the academic interest on the topic, scholars have increasingly called for the integration of the concept into regional innovation policy programs, mainly but not only in the context of the EU's smart specialisation strategy (S3) (Sbardella *et al.*, 2018, 2021, 2022; Balland and Boschma, 2019; Balland *et al.*, 2019; Pugliese *et al.*, 2019; Balland, 2022; Li and Rigby, 2022; Mewes and Broekel, 2022; Rigby *et al.*, 2022).

Notwithstanding the potential and promise of the new approaches I introduced above under the heading of knowledge complexity to approximate in some sense the quality of knowledge produced as well as the numerous calls to implement these measures into regional innovation policy, I believe there is still further need to substantiate these claims. There are some studies within the field that are empirically studying the extent of mid- to long-term productivity effects of regional complex knowledge. However, these papers tackle this question mainly indirectly by either analysing economic growth effects of regional specialisation into more complex knowledge and technology fields in general (Mewes and Broekel, 2022; Pintar and Scherngell, 2022) or by studying the growth effects of explicitly adopting a Balland *et al.* (2019) -type smart specialisation strategy that takes into account the complexity and relatedness of knowledge or technology fields targeted by inventors within a region (Li and Rigby, 2022; Rigby *et al.*, 2022). Few studies have so far attempted to directly analyse the differential positive productivity effect of complex knowledge production (Antonelli, Crespi and Quatraro, 2022) that is theoretically expected and would further legitimate the academic and policy interest in the topic of knowledge complexity.

On the other hand, there is an extensive empirical literature that presents evidence on the link between knowledge capital or more general knowledge production and productivity. Particular relevant works on this topic study this relationship at the firm (Griliches and Mairesse, 1984; Griliches, 1986; Mairesse and Sassenou, 1991; Raymond *et al.*, 2015), industry (Scherer, 1982; Griliches and Lichtenberg, 1984; Pakes and Schankerman, 1984), country (Coe and Helpman, 1995; Park, 1995; Coe, Helpman and Hoffmaister, 2009), or regional level (Döring and Schnellenbach, 2006; Fischer, Scherngell and Reismann, 2009; Antonelli, 2011; Scherngell, Borowiecki and Hu, 2014; Wanzenböck, 2017). The more recent studies draw on the rapidly growing empirical nexus of data to proxy knowledge production, such as patents and patent citations, publications or joint R&D projects. In general, these studies provide statistical

evidence on the relationship between knowledge production and productivity. However, this research inherently assumes – by means of the model specifications and variables used – that all knowledge has the same value, i.e. the quality of knowledge is neglected. In this paper we aim to remedy this by relating the regional production of complex knowledge to advances of a regional total factor productivity (TFP) index.

2. Theoretical framework and model

In order to explore the link between regional knowledge complexity and TFP, we adopt a spatial econometric modelling approach. Conceptually, the modelling approach is inspired by the extended regional knowledge capital model (KCM) that relates region-internal and regional-external knowledge to regional total factor productivity (Fischer, Scherngell and Reismann, 2009; LeSage and Fischer, 2012; Scherngell, Borowiecki and Hu, 2014). This extended version of the famous knowledge capital model (Griliches, 1979), includes knowledge spillovers in addition to internal knowledge capital in the production function.

Following the theoretical derivation in Scherngell et al. (2014), the extended regional knowledge capital model leads to an expression of regional output in the form of:

$$Q_{it} = L_{it}^{\alpha} C_{it}^{1-\alpha} K_{it}^{\beta_1} K_{it}^{*\beta_2} \quad (1)$$

Here, Q refers to regional output, L to labour input, C to capital input, K to region-internal and K^* to region-external knowledge. Alpha is the output elasticity with respect to labour and capital input. The indices i and t refer to region and time, respectively. As we believe that the quality of knowledge or knowledge complexity a region also needs to be taken into account, we further extend this model by including region internal and region external knowledge complexity.

$$Q_{it} = L_{it}^{\alpha} C_{it}^{1-\alpha} K_{it}^{\beta_1} K_{it}^{*\beta_2} C K_{it}^{\beta_3} C K_{it}^{*\beta_4} \quad (2)$$

As total factor productivity (TFP) is defined as output over conventional inputs (labour and capital), equation 2 leads to:

$$P_{it} = K_{it}^{\beta_1} K_{it}^{*\beta_2} C K_{it}^{\beta_3} C K_{it}^{*\beta_4} \quad (3)$$

This relates region internal and external knowledge capital as well as complex knowledge capital to regional total factor productivity. Taking the log form of this expression gives

$$p = \beta_1 k + \beta_2 Wk + \beta_3 ck + \beta_4 Wck \quad (4)$$

where lower case letters refer to logged (natural) variables. Here, region and time indices are dropped for visual convenience. This equation already gives us a starting point for our empirical modelling exercise to tease out whether knowledge capital and interestingly complex knowledge capital can be shown to be positively associated with regional TFP development. Because subnational regions are highly integrated into their environment in their economic but also knowledge creation activities (as mentioned above), we suspect that estimating a regional model according to equation 4 would suffer from omitted variable bias. This is likely the case as the spatial interconnectedness of regions is not well captured by the model. Following related literature (Elhorst, 2014a; Scherngell, Borowiecki and Hu, 2014) Scherngell et al (2014) we thus include the spatial lag of the dependent variable (TFP) to yield as spatial durbin model (SDM) of the form:

$$p = \rho Wp + \beta_1 k + \beta_2 Wk + \beta_3 ck + \beta_4 Wck \quad (5)$$

Following convention, rho refers to the coefficient of the spatial autoregressive process between neighbouring regions. Note that in this model, regional total factor productivity might be influenced by neighbouring productivity. The spatial weight matrix W defines the assumed neighbourhood structure of our model. We use the inverse of the bilateral distance between regions as the spatial weight. This means that two regions are assumed to be more connected if they are closer to each other. For details about the estimation and interpretation of a spatial durbin model, please refer to (LeSage and Pace, 2009; Elhorst, 2014b).

3. Data

In line with existing literature, we use patent data to proxy regional knowledge production. Specifically, we retrieve patent applications to the European Patent Office (EPO) by inventors located in the EU and EFTA countries, starting from 2000 to 2017 from the OECD REGPAT database (see Maraut *et al.*, 2008) which matches patents to NUTS-3 regions by inventor residence. We map patents located in these NUTS-3 regions to metropolitan regions as defined by EUROSTAT¹ and remove (fractional) patents that are located in peripheral regions with very few patents. See Pintar and Scherngell (2022) for details. These metropolitan regions represent more realistically functional economic regions. Metropolitan regions are combinations of NUTS-3 regions which are aggregated in a way to more realistically represent urban regions and to ideally come close to functional regions of cities, including commuter belts around a city.

Knowledge capital (k) is then defined as the five year sum of past regional patent applications. To account for the complexity of regional knowledge capital, we weight knowledge capital with the regional knowledge complexity index. To make this analysis comparable to related literature, we opt for using a popular measure of knowledge complexity, based on the Hidalgo and Hausmann economic complexity index (Hidalgo and Hausmann, 2009)².

We define the regional total factor productivity index (p) as in Caves *et al.* (1982).

$$p_{it} = (q_{it} - \bar{q}_t) - s(l_{it} - \bar{l}_t) - (1 - s)(c_{it} - \bar{c}_t) \quad (5)$$

Again, lower case letters refer to variables in logged form and an upper bar refers to yearly average values. Here, lower case s is the assumed share of labour costs in the production process. Similar to related studies (e.g. Beugelsdijk, Klasing and Milionis, 2018), we set s equal to 2/3. Regional output (q) is measured via real regional gross value added. Labour input (l) is the number of employees, adjusted by differences in the average working hours per country. The capital stock of a region is defined as the five year sum of past real gross fixed capital formation (investment). All non-patent variables described above are sourced from ARDECO³.

¹ See <https://ec.europa.eu/eurostat/web/metropolitan-regions/background>.

² Specifically, we use the knowledge complexity used in (Balland *et al.*, 2019; Pintar and Essletzbichler, 2022; Pintar and Scherngell, 2022).

³ ARDECO stands for Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy. See https://knowledge4policy.ec.europa.eu/territorial/ardeco-database_en. As we need to relate TFP to various knowledge capital, we need to translate economic variables also to the European metropolitan regions. GVA data and employment already comes in NUTS 3 data, so this can be easily aggregated to the needed spatial scale. Gross fixed capital formation (investment) is only available at the NUTS 2 level. Using NUTS 3 population data, we distribute investment data to NUTS 3 regions and then aggregate to the needed metropolitan regions.

4. Preliminary results

Following theoretical arguments mentioned in the introduction and the unnumerable number of quantitative studies on this subject, knowledge capital is shown to increase total factor productivity. However, most studies focus on explaining the relation between knowledge production and the level of TFP. To potentially substantiate claims of the recently popular literature on knowledge complexity and calls to integrate the focus on complex knowledge into regional innovation policies, we focus on the effect of knowledge capital and complex knowledge capital on the growth of TFP. Table 1 presents preliminary results of our modelling exercise. Here, models 1 to 3 refer to a simple linear model according to equation 4. As can be seen, this model is robust in the sense that the inclusion of only knowledge capital or complex knowledge capital or the combination of both leads to the same overall conclusion. Contrary to first belief, we find a negative association of the regional knowledge stock but to a higher extent the neighbouring knowledge capital on TFP growth.

Table 1: Estimation results

Dep. variable: 5 year tfp growth						
	OLS			ML		
	(1)	(2)	(3)	(4)	(5)	(6)
ln k	-0.0197 *		-0.0229 **	-0.0265 ***		-0.0279 ***
	(0.008)		(0.008)	(0.007)		(0.008)
W*ln k	-0.4197 ***		-0.3755 ***	-0.3285 ***		-0.3015 ***
	(0.040)		(0.040)	(0.038)		(0.039)
ln ck		-0.0007	-0.0014		-0.0013	-0.0014
		(0.001)	(0.001)		(0.001)	(0.001)
W*ln ck		0.1073 ***	0.0858 ***		0.0775 ***	0.0644 ***
		(0.014)	(0.014)		(0.013)	(0.013)
spatial lag				0.7639 ***	0.7802 ***	0.7231 ***
				(0.040)	(0.040)	(0.045)
no. regions	160	160	160	160	160	160
no. periods	13	13	13	13	13	13
Observations	2080	2080	2080	2080	2080	2080
twoway fixed effects	yes	yes	yes	yes	yes	yes
R ²	0.056	0.032	0.075			
Log. Likelihood				3498.331	3477.222	3511.447

Notes: The dependent variable is the five year difference of the tfp index as defined in the text. ln k and ln ck refer to the logged (natural) five year stock in knowledge and complex knowledge. The spatial weight matrix (W) is used to create spatially lagged version of the two variables of interest to account for (complex) knowledge spillovers. Model (4) to (6) are spatial durbin models (SDM) where "spatial lag" is the coefficient associated with the spatial lag of the dependent variable. Coefficients are statistically significant at the *p<0.05; **p<0.01; ***p<0.001 level.

While surprising at first, a negative size effect on growth is very common, for example in the growth and convergence literature (e.g. Piribauer and Crespo Cuaresma, 2016). Interestingly, the spillover effect is even higher in magnitude, possible indicating a competition effect between regions. Investigating the remaining spatial dependence in the residuals (via a Moran's I test) of model 3, confirmed our suspicions that a proper spatial modelling approach is needed. Models 4 to 6 refer to the spatial durbin model as in equation 5. First, we find that the spatial lag is positive and highly significant, indicating that the regional TFP development is highly dependent on the geographical position of the region. Again, we find negative associations of knowledge capital on TFP growth. However, while the region internal complex knowledge

stock seems to be unrelated with TFP growth, we find that a region might benefit from being located near regions that are able to produce highly complex knowledge.

5. Conclusion and limitations

In this paper we investigated whether knowledge capital and especially complex knowledge capital can be shown to be associated with future TFP growth. We adopted an extended regional KCM approach based on Scherngell et al. (2014) and introduced the concept of knowledge complexity to complement conventional measures of knowledge production. While this work is preliminary, we can identify that complex knowledge capital seems to show a different – and more favourable – relation with regional future TFP growth.

In this work we were limited by the data available. Especially the patent data used is somewhat outdated. In future work we will investigate the possibility to make more recent patent data usable in this framework. Moreover, we aim to improve the modelling approach by using different neighbourhood definitions and include a sweep of robustness tests.

Author contributions

Nico Pintar: Conceptualisation, Methodology, Software, Validation, Formal analysis, Data curation, Writing . Thomas Scherngell: Conceptualisation, Methodology, Validation, Supervision, Project administration, Funding acquisition.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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