Success breeds inequality: Innovation and income from a micro perspective of cities

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Introduction

Innovation is widely recognised as a catalyst for regional development. Investment in R&D and innovation activities increases productivity, thereby benefiting the income of individual firms. Through the process of knowledge spillovers, innovation affects entire economies, being a major agent of local and regional growth. However, knowledge creation is a cumulative process (Feldman, 1994), requiring recombination of existing ideas and combinatorial feedback (Weitzman, 1998). Therefore, knowledge is strongly rooted in existing technological trajectories (Balland et al., 2018) and thus highly spatially concentrated (Jaffe et al., 1993). This potentially generates challenges in the diffusion of innovations beyond knowledge sources (Fritsch & Wyrwich, 2021) if there is a shortage of talented researchers with absorptive and combinatorial capabilities (Adams & Clemmons, 2013). The lack of such capabilities causes problems in sharing tacit knowledge over long distances (Gertler, 2003), thus certain areas encompassing knowledge sources begin to isolate themselves with regard to innovation exchange (Jaffe et al., 1993).

The challenge of satisfactory knowledge diffusion is compounded by the increasing complexity of knowledge (Mewes & Broekel, 2020), as has been observed since at least the 19th century (Balland et al., 2020). In fact, it is the increasing number, intensity and uniqueness of knowledge combinations (Broekel, 2019) that causes difficulties for companies to assimilate, process and exploit the knowledge created in value chains or surrounding areas

(Yayavaram & Chen, 2015). This process is likely to intensify since there is a constant complexification of knowledge without sufficient support from human resources towards the acquisition of adequate capacity for assimilating and recombining knowledge components.

If, therefore, knowledge is indispensable for economic growth, its spatial scarcity will result in uneven growth in the incomes of companies and consequently of workers and owners. This will continue to be the case until knowledge becomes too complex, as is increasingly evident in developed countries. Despite the observed significant increase in the level of education and R&D intensity, faster economic growth has been increasingly less visible. This can be explained by the level of complexity of technology, which makes passive learning more difficult and increases expenditure on R&D and education, thus causing income growth to decline (Pintea & Thompson, 2007b).

These extremely complex processes of knowledge-based economic development have so far not been studied at the micro scale, i.e., spatially located enterprises. While differences in development levels have been studied in detail albeit at the level of regions or whole cities and their surrounding areas, within cities these processes still remain a mystery. In this study, we seek to explain the impact of emerging innovations on the level of income inequality inside 18 Polish provincial cities. We also consider the volatile impact of knowledge complexity on income inequalities. Deriving possible mechanisms of knowledge diffusion from the above theoretical considerations, we seek to test two hypotheses:

Hypothesis 1. Knowledge sources increase income in their vicinity to a greater extent than outside them, contributing to income inequality regardless of the level of entrepreneurship.

Hypothesis 2. Knowledge complexity from a certain threshold contributes to a relative reduction in the income of knowledge sources and thus a slower increase in income inequality, indicating the inverted-U shape of this relationship.

Data and methods

In hypothesis 1, we aim to analyse the impact of nascent innovations in knowledge sources on the level of per capita income of residents in the vicinity of these sources. There are two issues we need to take into consideration beforehand. First, the level of income may be driven by the intensity of economic activity, the impact of which we need to overrule in our study. Hence, we need to include the intensity of economic activity in the regression, which will explain part of residents' income. Second, we must consider a spatial shift between economic activity and the residence of the employees whose income we take as an explanatory variable. We therefore use the Spatial Durbin Error Model (SDEM), whose general expression is as follows:

$$\mathbf{Y}_{it} = \alpha + \mathbf{X}_{it}\beta + \mathbf{W}\mathbf{X}_{it}\theta + \mathbf{u}_{it},$$

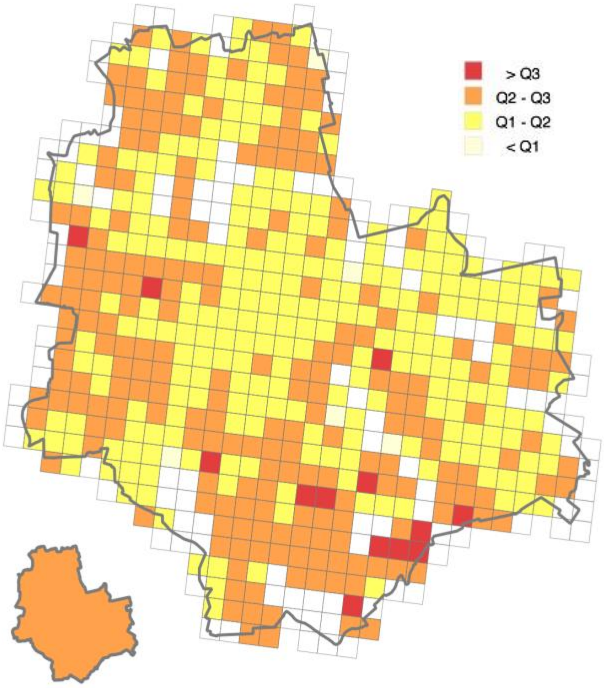
$$\mathbf{u}_{it} = \lambda\mathbf{W}\mathbf{u}_{it} + \boldsymbol{\varepsilon}_{it}$$

where θ is the coefficient of spatial autocorrelation, $\mathbf{Y}_{it}$ is the dependent variable of the data in i unit of observation do and time t, $\mathbf{X}_{it}$ is the independent variable of the data in i unit of observation and time t, $\mathbf{W}$ is the standardized spatial weighted row matrix, β is the coefficient of the independent variables, α is the intercept, λ is the coefficient of spatial error, $\mathbf{u}_{it}$ is the spatial error in i unit of observation at time t, and $\boldsymbol{\varepsilon}_{it}$ is the model error in i unit of observation and at time t.

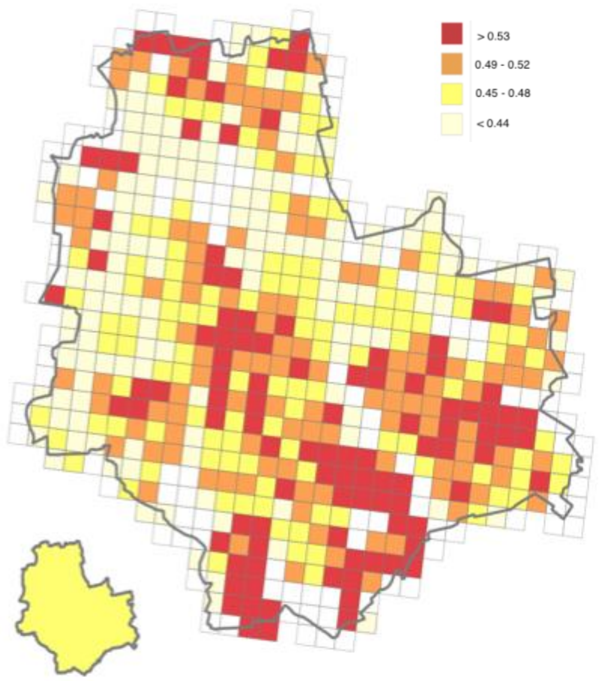
Our area of interest is intra-urban variation in the income situation of residents of provincial cities caused by the emergence of innovations in the local enterprises. Therefore, we analyse data divided into a grid of squares with an area of 1 square kilometre. In each grid area we have at our disposal several variables describing income disparities. Firstly, this is the average income level of residents per capita, which may be used to identify income disparities between neighbouring squares (spatial disparities). Second, it is the income spread of residents measured by the ratio P90/P10 or the income quintile diversity index of residents S80/S20. Third, it is the unevenness of the distribution of residents' incomes measured by the Gini coefficient. These data are taken from an experimental study conducted by Statistics Poland, examples of which are presented below. The data is available only for 2018.

Warsaw

Median income per capita in quantile bands

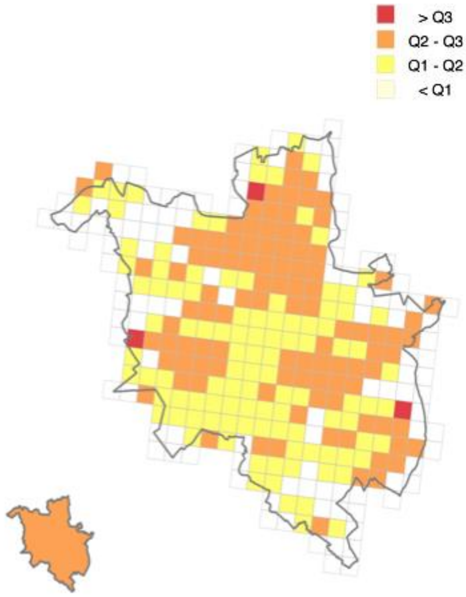


Gini index of income per capita

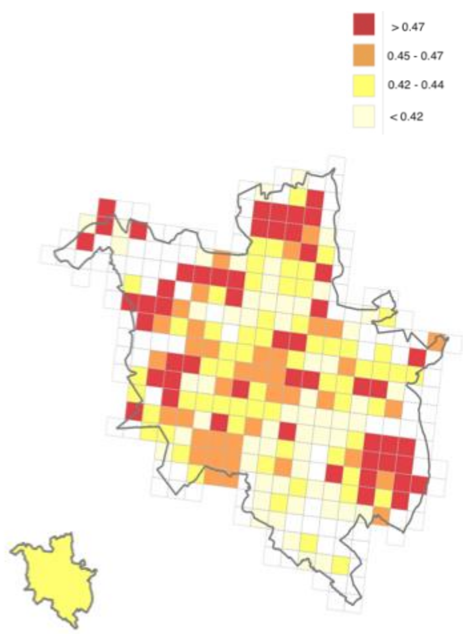


Poznań

Median income per capita in quantile bands



Gini index of income per capita



The main explanatory variable for income disparity in 2018 is the number of patents obtained by companies in the pre-2018 period, which covers the years 2000-2017, with the possibility of splitting the period into a shorter one, i.e., 2015–2017, 2010–2017 or 2005–2017. We also use variables relating to the complexity of knowledge in patents to test hypothesis 2, following the approach used in previous studies (Balland et al., 2018, 2020; Broekel, 2019; Mewes & Broekel, 2020; Pintea & Thompson, 2007a). We also employ a number of control variables such as business density, population density, structure of the economy, share of undeveloped land, etc. To this end, we draw on two linked databases. First, we utilize the Polish business register covering over eleven million firms (including agricultural firms). The database contains firm-level information including 5-digit NACE codes for primary and secondary codes, firm type, legal form, ownership, date of establishment and exact geolocation (longitude and latitude). The second database provided by the Polish Patent Office includes: patent number, patent classification (according to IPC), inventor, applicant, and assignee. Patents are linked to a company database indicating the exact location and NACE code to which the patent belongs. In addition, we use the Open Street Map database to calculate the structure and type of land use.

Bibliography

Adams, J. D., & Clemmons, J. R. (2013). How Rapidly Does Science Leak Out? A Study of the Diffusion of Fundamental Ideas. *Journal of Human Capital*, *7*(3), 191–229. https://doi.org/10.1086/673466

Balland, P.-A., Boschma, R., Crespo, J., & Rigby, D. L. (2018). Smart specialization policy in the European Union: Relatedness, knowledge complexity and regional diversification. *Regional Studies*, 1–17. https://doi.org/10.1080/00343404.2018.1437900

Balland, P.-A., Jara-Figueroa, C., Petralia, S. G., Steijn, M. P. A., Rigby, D. L., & Hidalgo, C. A. (2020). Complex economic activities concentrate in large cities. *Nature Human Behaviour*. https://doi.org/10.1038/s41562-019-0803-3

Broekel, T. (2019). Using structural diversity to measure the complexity of technologies. *PLOS ONE*, *14*(5), e0216856. https://doi.org/10.1371/journal.pone.0216856

Feldman, M. P. (1994). *The Geography of Innovation* (1st ed.). Springer. https://doi.org/10.1007/978-94-017-3333-5

Fritsch, M., & Wyrwich, M. (2021). Is innovation (increasingly) concentrated in large cities? An international comparison. *Research Policy*, *50*(6). https://doi.org/10.1016/j.respol.2021.104237

Gertler, M. S. (2003). Tacit knowledge and the economic geography of context, or The undefinable tacitness of being (there). *Journal of Economic Geography*, *3*(1), 75–99. https://doi.org/10.1093/jeg/3.1.75

Jaffe, A., Trajtenberg, M., & Henderson, R. (1993). Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *Quarterly Journal of Economics*, *108*(3), 577–598. https://doi.org/10.2307/2118401

Mewes, L., & Broekel, T. (2020). Technological complexity and economic growth of regions. *Research Policy*, 104156. https://doi.org/10.1016/j.respol.2020.104156

Pintea, M., & Thompson, P. (2007a). Technological complexity and economic growth. *Review of Economic Dynamics*, *10*(2), 276–293. https://doi.org/10.1016/j.red.2006.12.001

Pintea, M., & Thompson, P. (2007b). Technological complexity and economic growth. *Review of Economic Dynamics*, *10*(2), 276–293. https://doi.org/10.1016/j.red.2006.12.001

Weitzman, M. L. (1998). Recombinant Growth*. *The Quarterly Journal of Economics*, *113*(2), 331–360. https://doi.org/10.1162/003355398555595

Yayavaram, S., & Chen, W.-R. (2015). Changes in firm knowledge couplings and firm innovation performance: The moderating role of technological complexity. *Strategic Management Journal*, *36*(3), 377–396. https://doi.org/10.1002/smj.2218