Annex D. Patentable occupations

The proposal on adjusting innovation indicators for the occupational structure or rural economies comes from discussions with the OECD Expert Advisory Committee for Rural Innovation. During the sessions, several rural academics identified structural problems associated with how innovation is measured in rural areas and why the bias associated may not be territorially homogenous. To address this, work by Dotzel (2017[6]) and Wojan (2021[7]) proposes an occupation-driven approach for analysing regional invention. The authors argue that patenting rates should be computed on the subset of workers that might plausibly contribute to patenting. To do this, the authors regress the aggregate number of patents produced in the commuting zone during the period 2000-05 on the share of the workforce employed in a selection of detailed census occupations. The authors' commuting zone-level regression includes controls on the patent stock, human capital share (working-age population with a bachelor's degree or higher), population density, a natural amenity score and the wage-rental ratio. They apply the analysis to a core set of occupations (from the U.S. Department of Labor Employment and Training Administration O*NET database) defined by the National Science Foundation's classification of science, engineering and technical (SET) occupations, along with an iterative random selection of other occupations that may have a strong association with patenting. Ten thousand regressions are estimated with 19 non-SET occupations randomly included in each estimation. The inventive subset inclusion criteria for the non-SET occupations are those occupations-associated coefficients that are positive and significant in at least 75% of their regressions in the metro or non-metro analysis and are characterised as inventive. Of the 300 non-SET occupations included in the analysis, 11 are identified as inventive, that is consistently associated with positive, significant coefficients.

Table A D.1 provides a list of occupations with a relatively high probability of patent. Furthermore, Figure A D.1. demonstrate the distribution of these occupations as a share of the total employed population (patent intensity) across the United States. As demonstrated in Figure 3.4, adjusting for these shares reduces disparities in patenting intensities between territories. In comparison, patent intensity over total employment, over just knowledge-intensive or high-tech sectors provided in Figure A D.2. Adjusting denominators in patenting intensity (TL2), descriptively points towards the same direction, but statistically does not provide as powerful an argument. This could be due to loss of precision in TL2 level aggregation and relevance of the occupations included.

Table A D.1. Inventive occupations

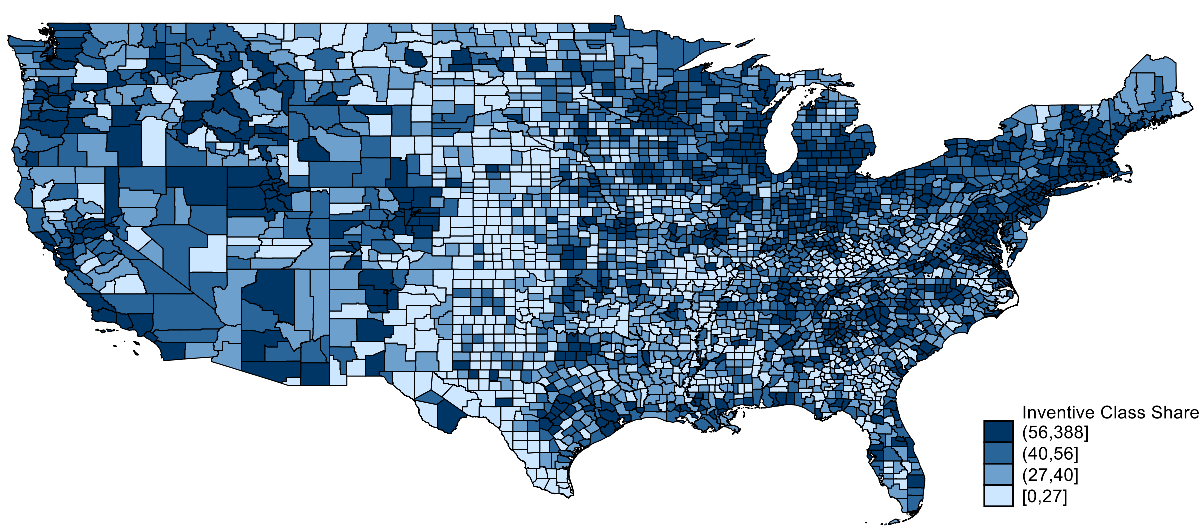
Occupations with a high (>75%) probability to patent

Census code(s)	Occupation
100-176, 190-196	Science, engineering, and technical (SET) occupations
005	Marketing and sales managers
030	Engineering managers
181	Market and survey researchers
263	Designers
284	Technical writers
772	Electrical, electronics and electromechanical assemblers
790	Computer control programmers and operators
803	Machinists
806	Model makers and patternmakers, metal and plastic
813	Tool and die makers
884	Semiconductor processors

Note: Occupations associated with coefficients that are positive and significant in at least 75% of their regressions in the metro or non-metro analysis are characterised as inventive.
Source: Dotzel, K. (2017[6]), "Three essays on human capital and innovation in the United States", Chapter 3, Graduate School of the Ohio State University; Wojan, T. (2021[7]), "An occupational approach for analyzing regional invention", National Center for Science and Engineering Statistics, https://ncses.nsf.gov/pubs/ncses22202/assets/ncses22202.pdf.

Figure A D.1. Inventive occupations in the US

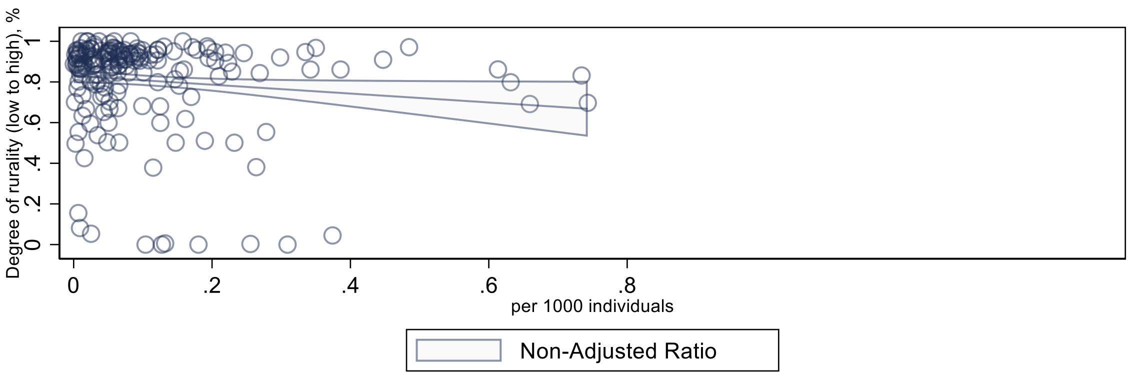
Shares on the county level



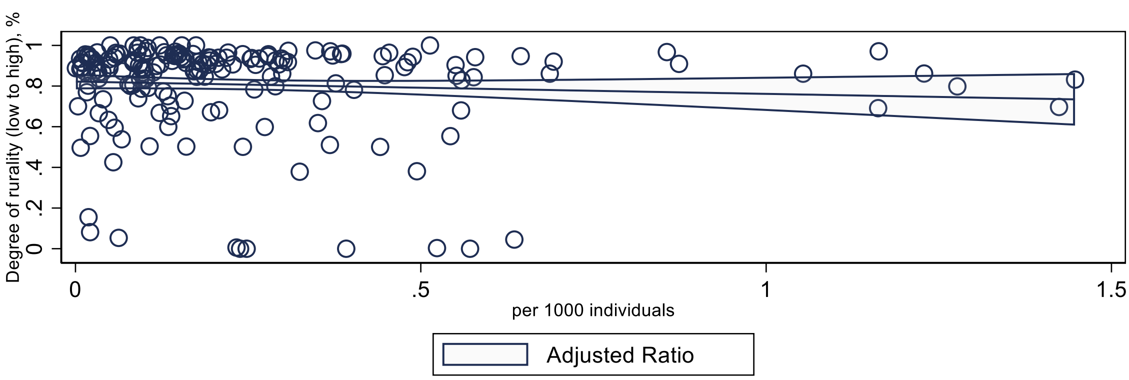
Note: Shares represent the shares of occupations likely to be patented as a part of all employed labour defined in Wojan (2021[7]).
Source: U.S. Census Bureau.

Figure A D.2. Adjusting denominators in patenting intensity (TL2)

Information and communication technology (ICT) patents to employment in knowledge-intensive and high-tech sectors (adjusted) ratios versus ICT patents to active labour force (15-64 year-olds) in OECD countries, 2019



A linear OLS regression estimate on the correlation between non-adjusted patent ratios and degree of rurality is .0014, but not-significantly different from 0 with a p-value of .973.



A linear OLS regression estimate of the correlation between adjusted patent ratios and degree of rurality is -.0008, but not-significantly different from 0 with a p-value of .99.

Note: The numerator in the ratios is the total number of patents in ICT per TL2 region. The denominator in the non-adjusted values is the total active labour force (15-64 year-olds). The denominator in the adjusted values is employment in knowledge-intensive sectors. The denominator in the non-adjusted ratios. The degree of rurality on the y-axis captures the percentage of individuals living in non-metropolitan regions within the TL2 regions. For visual purposes, outliers in degree of rurality and the respective ratios are omitted. Linear extrapolation was used for TL2 regions with missing values in 2019. Regression output on the correlation between each of the ratios and the degree of rurality for the reference year, 2019, includes country controls and lagged controls on productivity, real household income, education shares, elderly dependency ratios, population density, population growth and population gender differences.
Source: European Patent Office (PATSTAT[8]), OECD Regional Demography (database) (OECD[5]).

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