Society for the Study of Economic Inequality

Working Paper Series

Intergenerational Mobility of Education in Europe: Geographical Patterns, Cohort-Linked Measures, and the Innovation Nexus

Sarah McNamara

Guido Neidhöfer

Patrick Lehnert

ECINEQ 2024 664

ECINEQ 2024 664
2024 January
www.ecineq.org

Intergenerational Mobility of Education in Europe: Geographical Patterns, Cohort-Linked Measures, and the Innovation Nexus

Sarah McNamara
ZEW Mannheim
Guido Neidhöfer
ZEW Mannheim
Patrick Lehnert
University of Zurich

Abstract

We estimate intergenerational mobility of education for people born 1940-1999 at the subnational level for 40 European countries. The result is a panel of mobility indices for 105 mesoregions (NUTS1), and 215 microregions (NUTS2). We use these indices to make three contributions. First, we describe the geography of intergenerational mobility in Europe. Second, adapting a novel weighting procedure based on cohorts' relative economic contribution, we transform cohort-linked measures into annual measures of intergenerational mobility for each region. Third, we investigate the relationship between intergenerational mobility and innovation, and find robust evidence that higher mobility is associated with increased innovation.

Keyword: Intergenerational Mobility, Equality of Opportunity, Human Capital, Innovation, Regional Economic Performance, Europe

JEL Cassification: D63, I24, J62, O15

Intergenerational Mobility of Education in Europe: Geographical Patterns, Cohort-Linked Measures, and the Innovation Nexus

Sarah McNamara[1] Guido Neidhöfer[1,2] Patrick Lehnert[3]

[1] ZEW Mannheim, [2] Turkish-German University, [3] University of Zurich

This version: January 16, 2024

We estimate intergenerational mobility of education for people born 1940-1999 at the subnational level for 40 European countries. The result is a panel of mobility indices for 105 mesoregions (NUTS1), and 215 microregions (NUTS2). We use these indices to make three contributions. First, we describe the geography of intergenerational mobility in Europe. Second, adapting a novel weighting procedure based on cohorts' relative economic contribution, we transform cohort-linked measures into annual measures of intergenerational mobility for each region. Third, we investigate the relationship between intergenerational mobility and innovation, and find robust evidence that higher mobility is associated with increased innovation.

Keywords: Intergenerational Mobility, Equality of Opportunity, Human Capital, Innovation, Regional Economic Performance, Europe. **JEL-Classification**: D63, I24, J62, O15

Acknowledgments: We are grateful to Melanie Arntz, Joost De Laat, Elena Fumagalli, Uschi Backes-Gellner, Wolter Hassink, Friedhelm Pfeiffer, Joaquin Serrano, Jan Stuhler, Ulrich Zierahn-Weilage, and to participants of (virtual and in-person) seminars and conferences in Ispra, Istanbul, Mannheim, Montevideo, Rio de Janeiro, Utrecht, and Zurich for their valuable comments. Also, we would like to thank Clayton McNamara for his kind assistance with using the software used to construct the shape files and compute the maps. Guido Neidhöfer acknowledges the Jacobs Foundation for its support through a Jacobs Foundation Research Fellowship. Patrick Lehnert acknowledges funding from the Swiss State Secretariat for Education, Research and Innovation through its Leading House VPET-ECON (contract number 1315002234). Any remaining errors are our own.

Contacts and affiliations: Sarah McNamara is a Researcher at ZEW – Leibniz Centre for European Economic Research, Mannheim (sarah.mcnamara@zew.de). Guido Neidhöfer is a Visiting Professor of Economics at the Turkish-German University in Istanbul and a Senior Researcher at ZEW – Leibniz Centre for European Economic Research, Mannheim (guido.neidhoefer@zew.de). Patrick Lehnert is Assistant Professor for Personnel Economics at the University of Zurich (patrick.lehnert@business.uzh.ch).

1. Introduction

Intergenerational mobility has direct implications for individual well-being, equality of opportunity, and economic performance (e.g. Becker and Tomes, 1979; Corak, 2013; Galor and Zeira, 1993). If the circumstances into which individuals are born place fundamental constraints on the level of human capital they are likely to achieve, these constraints can lead to a mismatch between talent, education, and occupation (Rodriguez Mora, 2009). Indeed, empirical evidence shows that intergenerational mobility and equality of opportunity positively influence long-run growth and economic development (Marrero and Rodriguez, 2013; Neidhöfer et al., 2023).

In this paper, we draw the geography of intergenerational mobility of education in Europe, and focus on one channel potentially driving the relationship between mobility and growth, namely innovation. Suggestive evidence shows that intergenerational mobility is correlated with innovation (Aghion et al., 2019; Akcigit et al., 2017; Luo and Xie, 2023), that parental background and the local environment play an important role in the opportunity structure determining who becomes an inventor (Aghion et al., 2023; Bell et al., 2019), and that financial constraints based on parental background may harm economic growth by delivering inefficiencies in the allocation of talent and idea production (Akcigit et al., 2020). Our analysis provides the first large-scale evidence that the relationship between intergenerational mobility and innovation holds across European regions over time.

We proceed in three steps. First, we estimate the intergenerational mobility of education for cohorts born between 1940 and 1999 in European regions and illustrate geographical patterns. Second, adapting the procedure developed by Neidhöfer et al. (2023), we transform cohort-linked measures into annual measures of intergenerational mobility for each region. Third, we analyze the mobility-innovation nexus. Our results show that—conditional on regional development, structural change, cohort-specific initial conditions, and other factors potentially driving cross-regional heterogeneity—past intergenerational mobility is positively and significantly associated with contemporary innovation in terms of patent registration.

2. Data

To estimate intergenerational mobility of education, we use 10 waves of the European Social Survey (ESS) conducted between 2002 and 2020. The ESS is a representative cross-national survey in which 40 countries have participated in at least one round since the 2002/03 wave. Importantly, it includes questions about the level of education and retrospective questions on parental education, thus allowing us to measure intergenerational mobility while avoiding the bias associated with selectivity in co-residency samples (see e.g. Emran et al., 2018).[1] We pool all survey waves and apply survey design weights, normalizing the weights to make them consistent across waves (e.g. Neidhöfer et al., 2018). Furthermore, we restrict our sample to respondents who were at least 22 years old, and hence likely to have completed their education, when the survey was conducted.[2] Since migration could be endogenously related to both human capital allocation and economic performance within regions (e.g. Arntz et al., 2014), we exclude migrants.[3] Our final sample consists of 276,379 individuals.

In addition to the ESS, we use three further datasets to construct the variables for our empirical analysis. First, to measure regional innovation, our main outcome variable of interest, we rely on the number of patents as an established indicator of innovation performance (Trajtenberg, 1990). We retrieve patent count and citation-weighted patent count from the European Patent Office (EPO) at the country level, NUTS1 level, and NUTS2 level (or equivalent) from 1985 to 2015.

Second, to construct control variables for contemporary regional economic conditions, we use Lehnert et al.'s (2023) surface groups, a proxy for regional economic activity derived from daytime satellite imagery.[4] Using machine-learning techniques, the authors classify annual composites of Landsat satellite pixels from 1984 through 2020 into six different categories that describe terrestrial features of the earth with similar surface characteristics, the *surface groups* (built-up land, grassland, cropland, forest, land without buildings or vegetation, and water). These surface groups can be aggregated at any regional level and explain a large part of the variation in regional economic activity even at low levels of aggregation (Lehnert et al., 2023). We aggregate the surface groups to modified nested European NUTS boundary shapefiles.[5] This procedure thus provides us with a measure of regional economic activity that covers a longer time series than other proxies, such as night light intensity.

[1] In the case of missing information for one parent, we use the level of education of the available parent. Since years of schooling varies between countries, we use modified ISCED measures to generate a harmonized measure of years of schooling. Using the ESS-ISCED measure, available from wave 5 onward as the basis, we harmonize observations from earlier waves (see Online Appendix C).

[2] The analysis could be sensitive to this restriction if individuals had not yet completed their educational career. Suitable robustness checks imposing different age restrictions (e.g., older than 25) yield no significant changes in the main results.

[3] To increase the sample size, in our main estimation sample for intergenerational mobility we keep individuals with a migration background who did not themselves migrate to the country of residence (e.g., the children of migrants). Results excluding all individuals with a (direct or indirect) migration background are consistent; see Online Appendix B.

[4] This data is available for download at https://www.swissubase.ch/de/catalogue/studies/20253/19048/overview.

[5] Eurostat shapefiles were modified to include non-EU countries included in the ESS, i.e. Montenegro, Bosnia, Kosovo, Ukraine etc.; see Online Appendix C.

Third, we use the E-OBS database (Cornes et al., 2018) to control for cohort-specific initial conditions, or the past level of economic development that could have a direct effect on intergenerational mobility, as well as on future innovation and economic performance (e.g. Johnson and Papageorgiou, 2020). The database provides daily gridded land-only observational data for Europe, including blended time series measures of precipitation, temperature, sea level pressure, relative humidity, wind speed, and global radiation from 1950 to 2022. Since historical data on economic development is not available at the regional level for all European countries in our sample, our aim is to approximate the variation in economic conditions faced by cohorts using early-life weather conditions, which have been shown to have persistent effects on socioeconomic outcomes and economic growth (e.g. Dell et al., 2012; Maccini and Yang, 2009). Te reduce the number of variables included in our estimations, cohort-specific initial conditions are included as a single index variable, which summarizes the information on precipitation, temperature, sea level pressure, relative humidity, wind speed, and global radiation using factor analysis.

3. Empirical Strategy

We estimate the degree of intergenerational mobility of education for three cohorts—1940-59, 1960-79, and 1980-99—by regressing the years of education of individuals on those of their highest educated parent, controlling for sex and survey year fixed effects (e.g. Jäntti and Jenkins, 2015).[6] We will refer to this indicator of intergenerational mobility as the *slope coefficient*. Given potential distributional differences between the two generations, we multiply the slope coefficient with the ratio of standard deviations of parents' and children's years of education to obtain the *standardized persistence* as a second measure. These two measures are non-directional and origin-independent, capturing both upward and downward movements across the entire distribution. In both cases, the higher the indicator, the lower intergenerational mobility. Both measures are standard in the literature on intergenerational educational mobility and constitute valuable summary indicators for equality of (educational) opportunity (e.g. Blanden, 2013; Brunori et al., 2013). Results using the slope coefficient (included in the main text) and standardized persistence (included in the Online Appendix) are consistent.

To link intergenerational mobility and innovation, we adapt the method developed by Neidhöfer et al. (2023) to transform the cohort-specific mobility indicators into annual time-series measures, where the indicator value of a given cohort is weighted by the expected contribution of cohort members to the economy in a given year. To compute the weights attributed to each cohort for

[6] The subdivision of the sample into these cohorts enables us to estimate intergenerational educational mobility with a sufficiently large sample size of individuals for each country and region.

each year, we use the share of each cohort's effective labor supply over the total effective labor supply in a given year. We retrieve this weight from Mason et al. (2022), who estimate per-capita effective labor profiles over the life-cycle. To test the robustness of our results, we apply two further alternative weighting procedures. First, we use innovation life-cycle profiles for all patenting activity and, second, for highly cited patenting activity. We derive these patenting-based weights from Bell et al. (2016).[7] The results are consistent across all three weighting schemes. We display the results applying the weights derived from Mason et al. (2022) in the main text and the ones derived from Bell et al. (2016) in the Online Appendix.

To test whether higher levels of intergenerational mobility are associated with innovation at the regional level, we estimate a linear panel regression based on the time series for each region, including confounders potentially affecting the relationship between the two variables:

$$Y_{rt} = \alpha + \delta M_{rt} + \theta X_{rt-1} + \gamma I_{rt} + \tau_t + \gamma_r + \varepsilon_{rt} \quad (1)$$

Y is innovation in region r and year t. M is the degree of intergenerational mobility, as a weighted average of the mobility of the three cohorts (as previously described). X is a vector of contemporary controls for region-specific characteristics in $t-1$, namely proxy measures for local economic activity extracted from daytime satellite imagery collected via Landsat satellites (see Lehnert et al., 2023). I is a vector of controls for cohort-specific characteristics: average years of education, coefficient of variation of years of education, and cohort-specific initial conditions (see Section 2); again as a weighted average across the three cohorts. Fixed effects are included for year (τ) and region (γ).[8] ε is the error term.

The variation across years and regions is given by the interaction between intergenerational mobility and the weight, while, by construction, the applied methodology to compute *M* allows us to test one side of the relationship between intergenerational mobility and innovation avoiding issues related to reverse causality. Hence, the association between intergenerational mobility and innovation in the estimations is driven by cohorts with higher levels of mobility entering the labor market and gaining experience, while cohorts with lower mobility become older and reduce their labor force participation.

[7] For a more exhaustive explanation of the weighting procedure, see Online Appendix D.

[8] In one specification we control for country-specific time trends by including country dummies interacted with a linear time trend, instead of time fixed effects.

4. Results

4.1 Geography of intergenerational mobility in Europe

Figure 1 shows the geography of intergenerational mobility of education in Europe for the three cohorts that are the focus of our analysis. On average, from the oldest to the youngest cohort, the slope coefficient decreased by 0.108, indicating that mobility has increased.[9] To offer a more nuanced picture, the figure connects intergenerational mobility, measured by the slope coefficient (persistence), to educational inequality, measured by the coefficient of variation in years of schooling for each region and cohort. Regions with lower levels of intergenerational mobility tend to also exhibit a relatively high degree of educational inequality, implying the co-existence of inequality both within and between generations. This figure can broadly be understood to be the *Great Gatsby map* for Europe, in the spirit of Corak's (2013) graph, widely known as the "Great Gatsby curve". The correlation between persistence (measured by the slope coefficient) and inequality (measured by the coefficient of variation) in years of education across all cohorts is substantial; 0.61 and 0.39 at the country and NUTS2 level, respectively.

Interestingly, country borders are clearly visible on this map, which suggests that the degree of intergenerational mobility is mostly influenced by factors that act at the country level. The estimates also confirm the differences between Central and Northern Europe versus Southern and Eastern Europe, the former having higher mobility and lower inequality, and the latter having lower mobility and higher inequality (Hertz et al., 2008; Van der Weide et al., 2023). These differences change slightly over time but are largely persistent. The map also reveals a notable degree of heterogeneity in intergenerational mobility within countries among different regions. This heterogeneity underscores the significance of leveraging this variability at the subnational level to investigate the link between intergenerational mobility and economic performance.[10]

[9] Consistent with findings from other regions across the world (e.g., Hertz et al., 2008; Neidhöfer et al., 2018; Van der Weide et al., 2023), the change in mobility as measured by the other computed measure, the standardized persistence, which specifically captures alterations that affect the relative positions of families within the distribution, exhibits a relatively minor shift (an average decrease of 0.004 across all regions). This finding emphasizes that the observed increase in mobility primarily stems from improvements in educational achievements among individuals from less-educated families, with fewer changes in rank across the educational spectrum or downward mobility among individuals from highly educated families. For average estimates for each cohort and country, see Table A1 and A2 in Online Appendix A; all estimates for each cohort and region are included in the Data Appendix.

[10] Various factors may account for these distinct patterns across countries and regions, including variations in institutions, educational systems, tracking methods, public education spending, and segregation, among others. However, isolating these factors and providing comprehensive evidence regarding their impact on intergenerational mobility is beyond the scope of this study. For comprehensive discussions on the potential channels influencing the transmission of socio-economic advantages across generations, see Heckman and Mosso (2014) and Stuhler (2018).

4.2 Intergenerational Mobility and Innovation

In this section we test the relationship between intergenerational mobility of education and innovation.[11] Table 1 presents our preferred estimates, where intergenerational mobility (*M*) is measured by the slope coefficient, and innovation, the dependent variable, by the inverse hyperbolic sine of the number of patents.[12] Estimates using standardized persistence, the number of citation-weighted patents, or different weighting schemes to obtain the annual measures of mobility are robust and consistent with these results.[13]

The consistently negative and significant coefficient of *M*—after controlling for potential covariates, regional heterogeneity, cohort-specific initial conditions, and country-specific trends—shows that higher levels of intergenerational mobility (i.e., a lower slope coefficient) are strongly associated with more innovation. With the inclusion of control variables, the coefficient of interest decreases significantly. Nevertheless, in our more parsimonious model specifications, incorporating region and time fixed effects or country-specific time trends that greatly contribute to explaining the variation in the number of patents, as evidenced by the noticeable increase in the adjusted R-squared values, the coefficient of *M* remains significant and substantial in size.

To interpret the size of the association, we estimate the elasticity derived from the point estimate following the procedure described in Bellemare and Wichman (2019). A decrease of the slope coefficient by 0.1, which is very close to the average change experienced by European regions from the oldest to the youngest cohort in our sample, is associated with a positive change in the number of patents between 4.7% and 19%. This provides suggestive evidence that the positive impact of improved intergenerational mobility on innovation is economically significant.

[11] We use an augmented NUTS 1 definition of a regional unit that takes a hierarchical approach to spatial scale: For those regions that are a single country at the NUTS 0, 1 and 2 levels, or equivalent for non-EU countries, they enter the analysis as whole countries. For those regions where the whole country is one unit at the NUTS 1 level but not at the NUTS 2 level, we default to the NUTS 2 definition of regions. For all other cases, we use the NUTS 1 or equivalent level. Changing this specification, for instance by excluding countries where we have no estimates at a disaggregated level, yields consistent results.

[12] We use the hyperbolic sine because it offers a similar interpretation as taking the logarithm, while allowing the inclusion of values equal to zero (see Bellemare and Wichman, 2019).

[13] Results presented in this section are based on weighting intergenerational mobility measures with the per-capita effective labor profiles over the life-cycle method, the other two methods described in Section 3 are retained for robustness checks. Further, to test for sensitivity in the measured relationship based on the selected sample, we estimate results additionally excluding those individuals with a migration background (i.e., where one or more parent had a migration experience). The results are robust to the utilization of all alternative specifications, with additional results presented in Online Appendix B.

5. Conclusions

Theoretical models and empirical research show that intergenerational mobility is a driver of economic growth and development. In this paper, we provide a panel of indices for intergenerational mobility in European regions that can be used in future research to investigate these relationships further. Our findings provide suggestive evidence that one driver of this relationship is that intergenerational mobility fosters innovation. This result is in line with the theoretical argument that improving equality of opportunity contributes to a better allocation of talent and abilities, and eventually improves the efficiency of economic systems (e.g. Galor and Moav, 2004; Galor and Tsiddon, 1997; Galor and Zeira, 1993; Hassler and Rodriguez Mora, 2000). While we cannot entirely dismiss the potential influence of unobserved sources of heterogeneity not accounted for in our estimations, we believe that these findings, and the new data source that we provide, significantly contribute to our understanding of the relationship between intergenerational mobility and economic performance.

References

Aghion, P., Akcigit, U., Bergeaud, A., Blundell, R., & Hémous, D. (2019). Innovation and top income inequality. Review of Economic Studies, 86(1), 1–45.

Aghion, P., Akcigit, U., Hyytinen, A., & Toivanen, O. (2023). 2022 Klein Lecture Parental Education and Invention: The Finnish Enigma. International Economic Review.

Akcigit, U., Grigsby, J., & Nicholas, T. (2017). The rise of American ingenuity: Innovation and inventors of the golden age. Technical report, National Bureau of Economic Research, Cambridge.

Akcigit, U., Pearce, J. G., & Prato, M. (2020). Tapping into talent: Coupling education and innovation policies for economic growth. NBER working paper No. w27862.

Arntz, M., Gregory, T., & Lehmer, F. (2014). Can Regional Employment Disparities Explain the Allocation of Human Capital Across Space? Regional Studies, 48(10), 1719-1738.

Becker, G. S., & Tomes, N. (1979). An equilibrium theory of the distribution of income and intergenerational mobility. Journal of Political Economy, 87(6), 1153-1189.

Bell, A., Chetty, R., Jaravel, X., Petkova, N., & Van Reenen, J. (2016). The Lifecycle of Inventors. SSRN Electronic Journal.

Bell, A., Chetty, R., Jaravel, X., Petkova, N., & Van Reenen, J. (2019). Who Becomes an Inventor in America? The Importance of Exposure to Innovation. The Quarterly Journal of Economics, 134(2), pp. 647–713.

Bellemare, M. F., & Wichman, C. J. (2020). Elasticities and the inverse hyperbolic sine transformation. Oxford Bulletin of Economics and Statistics, 82(1), 50-61.

Blanden, J. (2013). Cross-Country Rankings in Intergenerational Mobility: a Comparison of Approaches from Economics and Sociology. Journal of Economic Surveys, 27(1), pp. 38–73.

Brunori, P., Ferreira, F. H., & Peragine, V. (2013). Inequality of opportunity, income inequality, and economic mobility: Some international comparisons. In Getting development right: Structural transformation, inclusion, and sustainability in the post-crisis era (pp. 85-115). New York: Palgrave Macmillan US.

Corak, M. (2013). Income Inequality, Equality of Opportunity, and Intergenerational Mobility. Journal of Economic Perspectives, 27(3), pp. 79–102.

Cornes, R., van der Schrier, G., van den Besselaar, E., & Jones, P. (2018). An Ensemble Version of the E-OBS Temperature and Precipitation Data Sets. Journal of Geophysical Research: Atmospheres, 123(17), pp. 9391–9409.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. American Economic Journal: Macroeconomics, 4, 66–95.

Emran, M., Greene, W., & Shilpi, F. (2018). When Measure Matters: Coresidency, Truncation Bias, and Intergenerational Mobility in Developing Countries. Journal of Human Resources, 53(3), pp. 589–607.

Galor, O., & Moav, O. (2004). From physical to human capital accumulation: Inequality and the process of development. The Review of Economic Studies, 71(4), 1001-1026.

Galor, O., & Tsiddon, D. (1997). Technological Progress, Mobility and Economic Growth. American Economic Review, 87(3), pp. 363–382.

Galor, O., & Zeira, J. (1993). Income distribution and macroeconomics. The Review of Economic Studies, 60(1), 35-52.

Hassler, J., & Rodríguez Mora, J. (2000). Intelligence, Social Mobility, and Growth. American Economic Review, 90(4), pp. 888–908.

Heckman, J. J., & Mosso, S. (2014). The economics of human development and social mobility. Annual Review of Economics, 6, 689–733.

Hertz, T., Jayasundera, T., Piraino, P., Selcuk, S., Smith, N., & Verashchagina, A. (2008). The Inheritance of Educational Inequality: International Comparisons and Fifty-Year Trends. The B.E. Journal of Economic Analysis & Policy, 7(2).

Jäntti, M., & Jenkins, S. (2015). Income Mobility. In A.B. Atkinson and F. Bourguignon (Eds.), Handbook of Income Distribution. Elsevier, pp. 807–935.

Johnson, P., & Papageorgiou, C. (2020). What remains of cross-country convergence? Journal of Economic Literature, 58, 129–75.

Lehnert, P., Niederberger, M., Backes-Gellner, U., & Bettinger, E. (2023). Proxying Economic Activity with Daytime Satellite Imagery: Filling Data Gaps across Time and Space. PNAS Nexus, 2(4).

Luo, C., & Xie, L. (2023). Regional intergenerational mobility and corporate innovation: Evidence from China. PLOS ONE, 18(4), pp. e0283588–e0283588.

Maccini, S., & Yang, D. (2009). Under the weather: Health, schooling, and economic consequences of early-life rainfall. American Economic Review, 99, 1006–26.

Marrero, G. A., & Rodríguez, J. G. (2013). Inequality of opportunity and growth. Journal of Development Economics, 104, 107-122.

Mason, A., Lee, R., & NTA Network. (2022). Six ways population change will affect the global economy. Population and Development Review, 48(1), 51-73.

Neidhöfer, G., Ciaschi, M., Gasparini, L., & Serrano, J. (2023). Social mobility and economic development. Journal of Economic Growth, 1-33.

Neidhöfer, G., Serrano, J., & Gasparini, L. (2018). Educational inequality and intergenerational mobility in Latin America: A new database. Journal of Development Economics, 134, 329-349.

Rodríguez Mora, J. V. (2009). The Misallocation of Talent. CREI, Centre de Recerca en Economia Internacional.

Stuhler, J. (2018). A review of intergenerational mobility and its drivers. Technical Report, Publications Office of the European Union, Luxembourg.

Trajtenberg, M. (1990). A penny for your quotes: Patent citations and the value of innovations. The RAND Journal of Economics, 21(1), 172-187.

Van der Weide, R., Lakner, C., Mahler, D. G., Narayan, A., & Gupta, R. (2024). Intergenerational mobility around the world: A new database. Journal of Development Economics, 166, 103167.

TABLES & FIGURES

Table 1. Intergenerational Mobility and Innovation at the Augmented NUTS1 Level

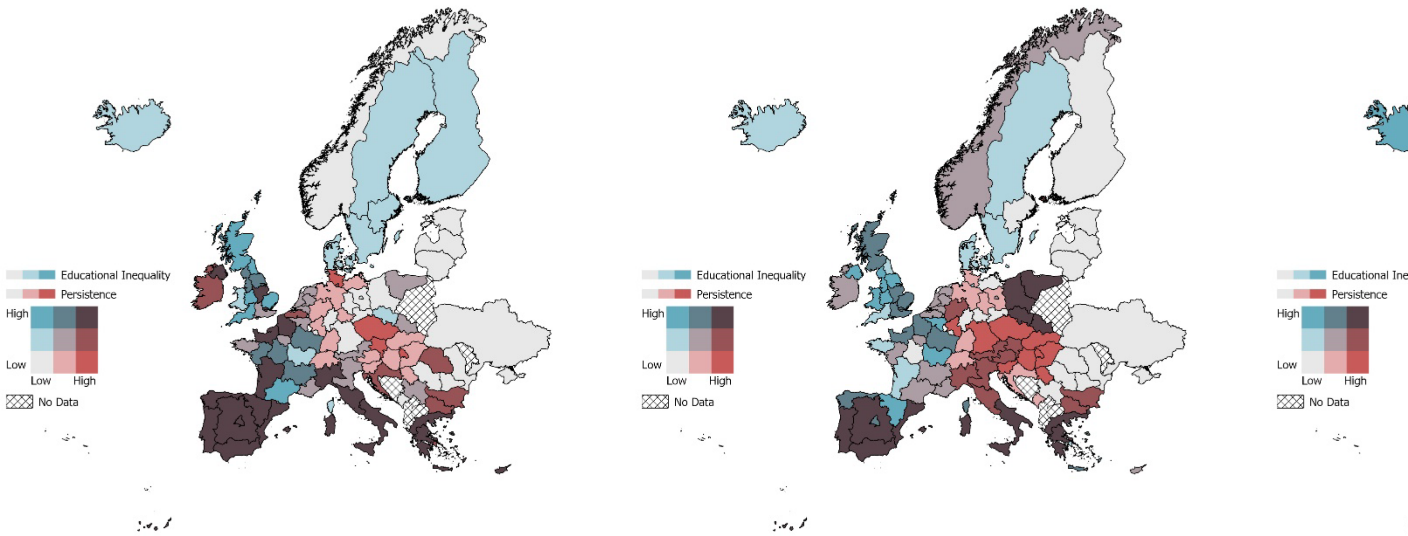
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
M *(Slope Coefficient)*	-4.193***	-2.629***	-2.887***	-2.725***	-2.574***	-1.443***	-1.061**
	(0.294)	(0.315)	(0.346)	(0.319)	(0.315)	(0.399)	(0.414)
Cohort Controls		X	X	X	X	X	X
Cohort-Specific Initial Conditions			X	X	X	X	X
Contemporary Controls				X	X	X	X
Year F.E.					X	X	
Reg F.E.						X	X
Country-Specific Time Trend							X
Observations	3859	3859	3859	3747	3747	3747	3747
Adjusted R-squared	0.0638	0.154	0.155	0.166	0.180	0.942	0.962
Elasticity	-1.870	-1.173	-1.288	-1.216	-1.148	-0.644	-0.473

Notes: Sample consists of regions over time. Dependent variable is the asymptotic sine transformation of the number of registered patents. M is the slope coefficient, applying cohort-participation weights. Cohort controls are average and coefficient of variation of years of education. Cohort specific initial conditions include a summary indicator for historical precipitation, temperature, sea level pressure, relative humidity, wind speed, and global radiation associated with the respective cohorts, also weighted by cohort-participation weights. Contemporary controls include variables indicative of structural transformation and local development retrieved from Lehnert et al. (2023). Last row shows the elasticity computed based on the regression coefficient applying the procedure explained in Bellemare and Wichman (2019). Standard errors obtained by bootstrapping with 100 replications. *p<.1, **p<.05, ***p<.01. *Source*: see data section; own calculations.

Figure 1. The Geography of Intergenerational Mobility and Educational Inequality in

(a) Cohort 1940-59

(b) Cohort 1960-79



Notes: Figures (a) to (c) illustrate the bivariate distribution of intergenerational mobility, as measured by the slope coefficient, versus educational inequality, measured by the
1960-79 and 1980 to 1999 cohorts, respectively. The axes indicate terciles, and results are reported at the NUTS 1 level with the addition of Ukraine. Use of terciles demonstra
Source: ESS 2002-2020. Own calculations. Shape files modified to include non-NUTS regions (see online Appendix C).

ONLINE APPENDIX

Intergenerational Mobility of Education in Europe: Geographical Patterns, Cohort-Linked Measures, and the Innovation Nexus

Sarah McNamara, Guido Neidhöfer, Patrick Lehnert

APPENDIX A – Descriptive Statistics

Table A1. Intergenerational Mobility in Europe: Slope Coefficient

	Cohort 1940-59		1960-79		1980-99	
	Coeff.	Std. Dev.	Coeff.	Std. Dev.	Coeff.	Std. Dev.
Albania	.383	.093	.429	.054	.600	.087
Austria	.514	.013	.537	.033	.570	.031
Belgium	.503	.018	.367	.015	. 385	.018
Bulgaria	.642	.018	.545	.019	.531	.025
Croatia	.531	.022	.393	.020	.393	.029
Cyprus	.655	.036	.417	.024	. 212	.035
Czech Republic	.519	.019	.492	.016	.382	.019
Denmark	.380	.021	.337	.019	.234	.026
Estonia	.265	.014	.272	.013	.403	.019
Finland	.360	.015	.243	.014	.189	.017
France	.480	.018	.372	.014	.321	.020
Germany	.422	.021	.414	.019	.313	.019
Greece	.644	.037	.421	.020	.355	.027
Hungary	.497	.016	.582	.016	.617	.023
Iceland	.243	.027	.292	.030	.219	.033
Ireland	.558	.017	.393	.014	.392	.022
Italy	.650	.026	.504	.016	.382	.020
Kosovo	.619	.119	.395	.043	.283	.088
Latvia	.260	.034	.208	.035	.380	.056
Lithuania	.270	.016	.210	.015	.312	.029
Montenegro	.540	.053	.492	.044	.557	.053
Netherlands	.434	.018	.397	.017	.315	.020
North Macedonia	.635	.103	.436	.055	.379	.052
Norway	.352	.019	.360	.018	.270	.027
Poland	.458	.019	.580	.019	.436	.019
Portugal	.773	.038	.674	.029	.392	.023
Romania	.160	.031	.116	.024	.179	.042
Serbia	.504	.039	.392	.034	.573	.050
Slovakia	.499	.030	.519	.026	.518	.036
Slovenia	.478	.021	.447	.018	.213	.024
Spain	.702	.022	.489	.013	.335	.019
Sweden	.333	.015	.294	.017	.253	.024
Switzerland	.418	.020	.394	.021	.336	.027
Turkey	.768	.052	.647	.051	.556	.046
Ukraine	.310	.019	.392	.022	.361	.046
United Kingdom	.413	.018	.334	.016	.297	.024

Source: ESS 2002-2020. Own calculations. Indices computed cohort-wise by pooling all survey waves and applying design weights. Standard errors obtained by bootstrapping with 100 replications.

Table A2. Intergenerational Mobility in Europe: Standardized Persistence

	Cohort 1940-59		1960-79		1980-99	
	Coeff.	Std. Dev.	Coeff.	Std. Dev.	Coeff.	Std. Dev.
Albania	.349	.080	.536	.058	.487	.055
Austria	.489	.029	.456	.029	.541	.029
Belgium	.504	.016	.456	.019	.483	.021
Bulgaria	.628	.013	.583	.017	.573	.021
Croatia	.551	.019	.499	.021	.411	.029
Cyprus	.371	.022	.478	.022	.265	.043
Czech Republic	.464	.017	.464	.014	.408	.019
Denmark	.413	.021	.407	.022	.278	.031
Estonia	.344	.019	.334	.015	.404	.019
Finland	.350	.014	.357	.019	.234	.020
France	.451	.016	.443	.016	.408	.024
Germany	.350	.016	.380	.017	.338	.020
Greece	.384	.024	.402	.015	.463	.026
Hungary	560	.017	.587	.017	.611	.019
Iceland	.261	.029	.288	.029	.230	.033
Ireland	.480	.012	.467	.014	.476	.023
Italy	.528	.020	.525	.017	.462	.020
Kosovo	.410	.076	.439	.045	.319	.095
Latvia	.323	.039	.262	.042	.392	.057
Lithuania	329	.020	.320	.024	.346	.030
Montenegro	.557	.060	.567	.045	.521	.045
Netherlands	.416	.016	.423	.018	.357	.021
North Macedonia	.514	.070	.544	.046	.457	.060
Norway	.399	.021	.394	.019	.270	.028
Poland	.446	.019	.507	.017	.442	.018
Portugal	.437	.026	.444	.017	.409	.024
Romania	.202	.041	.209	.040	.278	.063
Serbia	.529	.037	.520	.035	.557	.041
Slovakia	.494	.027	.507	.024	.516	.035
Slovenia	.481	.019	.476	.017	.227	.025
Spain	.479	.020	.456	.013	.397	.022
Sweden	.366	.017	.402	.023	.333	.028
Switzerland	.418	.019	.385	.020	.347	.027
Turkey	.415	.056	.380	.031	.421	.039
Ukraine	.412	.023	.395	.029	.333	.041
United Kingdom	.367	.016	.400	.018	.353	.027

Source: ESS 2002-2020. Own calculations. Indices computed cohort-wise by pooling all survey waves and applying design weights. Standard errors obtained by bootstrapping with 100 replications.

Table A3. Variables used in main estimations

Variables	Measure	Source
Dependent variables	- Patent counts - Citation-weighted patent counts	EPO
Main independent variables	- Slope coefficient (regression of parents' on children's years of education) - Standardized persistence (slope coefficient multiplied by ratio of standard deviations of parents' and children's years of education)	Own estimations using ESS
Cohort controls	- Average years of education - Coefficient of variation of years of education	Own estimations using ESS
Contemporary controls	- Built-up area, crops area, forest area, grass area, no vegetation area, water area, cloud area (all in log pixel count)	Own estimations using the procedure and data explained in Lehnert et al. (2023)
Cohort-specific initial conditions	- Historical precipitation, temperature, sea level pressure, relative humidity, wind speed, and global radiation associated with the respective cohorts. Summarized by factor analysis	E-OBS

APPENDIX B – Robustness

Table B1. Intergenerational Mobility and Innovation - Alternative Specifications I

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable: Patents (arcsinhh) / Indep. Variable M: Standardized Persistence							
M	-2.884***	-3.281***	-3.504***	-3.316***	-3.078***	-0.302	-1.808***
	(0.409)	(0.406)	(0.445)	(0.387)	(0.387)	(0.362)	(0.463)
Observations	3859	3859	3859	3747	3747	3747	3747
Adjusted R-squared	0.0160	0.156	0.157	0.167	0.181	0.942	0.962
Elasticity	-1.219	-1.388	-1.482	-1.402	-1.302	-0.128	-0.765
Dep. Variable: Citation weighted patents (arcsinhh) / Indep. Variable M: Slope Coefficient							
M	-4.328***	-2.647***	-2.738***	-2.562***	-2.489***	-1.208**	-1.027
	(0.332)	(0.351)	(0.385)	(0.356)	(0.346)	(0.510)	(0.767)
Observations	3859	3859	3859	3747	3747	3747	3747
Adjusted R-squared	0.0554	0.154	0.154	0.160	0.196	0.916	0.904
Elasticity	-1.946	-1.190	-1.231	-1.152	-1.119	-0.543	-0.462
Dep. Variable: Citation weighted patents (arcsinhh) / Indep. Variable M: Standardized Persistence							
M	-2.825***	-3.275***	-3.328***	-3.151***	-2.997***	-0.204	-2.289***
	(0.453)	(0.446)	(0.488)	(0.414)	(0.407)	(0.474)	(0.833)
Observations	3859	3859	3859	3747	3747	3747	3747
Adjusted R-squared	0.0124	0.156	0.156	0.161	0.197	0.916	0.904
Elasticity	-1.204	-1.396	-1.418	-1.343	-1.277	-0.0872	-0.976
Cohort Controls		X	X	X	X	X	X
Cohort-Specific Initial Conditions			X	X	X	X	X
Contemporary Controls				X	X	X	X
Year F.E.					X	X	
Reg F.E.						X	X
Country-Specific Time Trends							X

Notes: Sample consists of regions over time. Cohort controls are average and coefficient of variation of years of education. Cohort-specific initial conditions include a summary indicator for historical precipitation, temperature, sea level pressure, relative humidity, wind speed, and global radiation associated with the respective cohorts, also weighted by cohort-participation weights. Contemporary controls include variables indicative of structural transformation and local development retrieved from Lehnert et al. (2023). Last row shows the elasticity computed based on the regression coefficient applying the procedure explained in Bellemare and Wichman (2019). Standard errors obtained by bootstrapping with 100 replications. *p<.1, **p<.05, ***p<.01. *Source*: see data section; own calculations.

Table B2. Intergenerational Mobility and Innovation - Alternative Specifications II

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Alternative cohort-participation weights (age-innovation profile I)							
Dep. Variable: Patents (arcsinhh) / Indep. Variable M: Slope Coefficient							
M	-3.832***	-2.280***	-2.478***	-2.383***	-2.108***	-0.936***	-0.734**
	(0.281)	(0.300)	(0.331)	(0.338)	(0.338)	(0.312)	(0.324)
Observations	3859	3859	3859	3754	3754	3754	3754
Adjusted R-squared	0.0568	0.154	0.155	0.162	0.179	0.942	0.962
Elasticity	-1.734	-1.032	-1.121	-1.078	-0.954	-0.424	-0.332
Dep. Variable: Patents (arcsinhh) / Indep. Variable M: Standardized Persistence							
M	-2.613***	-3.027***	-3.202***	-3.125***	-2.729***	-0.0260	-1.069***
	(0.403)	(0.399)	(0.440)	(0.377)	(0.386)	(0.344)	(0.353)
Observations	3859	3859	3859	3754	3754	3754	3754
Adjusted R-squared	0.0134	0.158	0.158	0.165	0.182	0.942	0.962
Elasticity	-1.108	-1.284	-1.358	-1.325	-1.158	-0.0110	-0.454
Alternative cohort-participation weights (age-innovation profile II)							
Dep. Variable: Patents (arcsinhh) / Indep. Variable M: Slope Coefficient							
M	-4.025***	-2.477***	-2.665***	-2.581***	-2.393***	-1.088***	-0.544**
	(0.282)	(0.300)	(0.325)	(0.280)	(0.274)	(0.260)	(0.266)
Observations	3859	3859	3859	3743	3743	3743	3743
Adjusted R-squared	0.0623	0.158	0.159	0.167	0.178	0.942	0.961
Elasticity	-1.800	-1.108	-1.192	-1.155	-1.071	-0.487	-0.243
Dep. Variable: Patents (arcsinhh) / Indep. Variable M: Standardized Persistence							
M	-2.700***	-3.103***	-3.263***	-3.112***	-2.828***	-0.0802	-0.566*
	(0.398)	(0.393)	(0.429)	(0.384)	(0.384)	(0.273)	(0.292)
Observations	3859	3859	3859	3743	3743	3743	3743
Adjusted R-squared	0.0146	0.160	0.160	0.168	0.178	0.941	0.961
Elasticity	-1.143	-1.313	-1.381	-1.317	-1.197	-0.0340	-0.240
Cohort Controls		X	X	X	X	X	X
Cohort-Specific Initial Conditions			X	X	X	X	X
Contemporary Controls				X	X	X	X
Year F.E.					X	X	
Reg F.E.						X	X
Country-Specific Time Trends							X

Notes: Sample consists of regions over time. Weights with age-innovation profiles are based on innovation life-cycle profiles for all patenting activity (profile I) and highly cited patents (profile II), both derived from Bell et al. (2016). Cohort controls are average and coefficient of variation of years of education. Cohort specific initial conditions include a summary indicator for historical precipitation, temperature, sea level pressure, relative humidity, wind speed, and global radiation associated with the respective cohorts, also weighted by cohort-participation weights. Contemporary controls include variables indicative for structural transformation and local development retrieved from Lehnert et al. (2023). Standard errors obtained by bootstrapping with 100 replications. *p<.1, **p<.05, ***p<.01. *Source*: see data section; own calculations.

Table B2. Intergenerational Mobility and Innovation - Alternative Specifications III

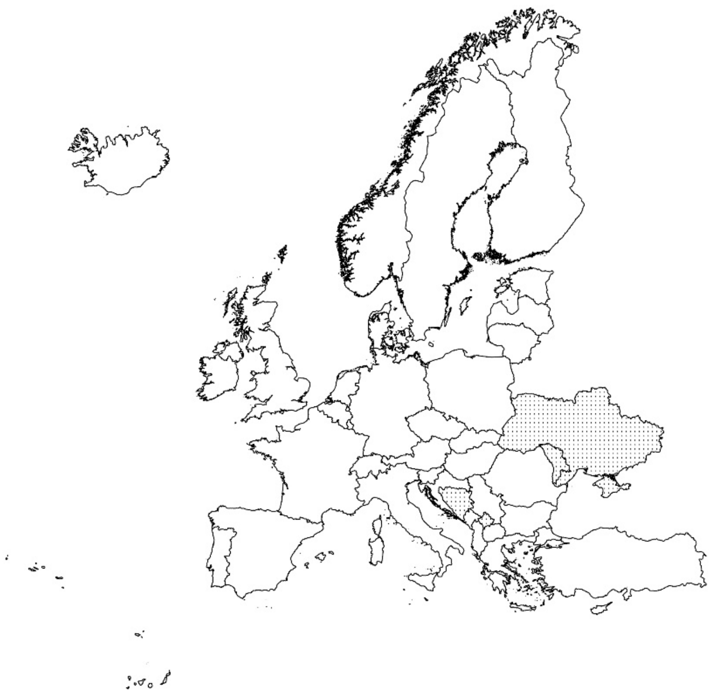
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Excluding all individuals with migration background							
Dep. Variable: Patents (arcsinhh) / Indep. Variable M: Slope Coefficient							
M	-4.604***	-3.222***	-3.544***	-3.541***	-3.413***	-2.757***	-1.273***
	(0.299)	(0.352)	(0.383)	(0.341)	(0.343)	(0.376)	(0.397)
Observations	3859	3859	3859	3747	3747	3747	3747
Adjusted R-squared	0.0713	0.154	0.156	0.160	0.177	0.942	0.962
Elasticity	-2.053	-1.437	-1.581	-1.579	-1.522	-1.229	-0.567
Dep. Variable: Patents (arcsinhh) / Indep. Variable M: Standardized Persistence							
M	-3.265***	-3.332***	-3.482***	-3.496***	-3.298***	-0.920**	-1.038**
	(0.392)	(0.406)	(0.439)	(0.399)	(0.391)	(0.406)	(0.432)
Observations	3859	3859	3859	3747	3747	3747	3747
Adjusted R-squared	0.0182	0.150	0.150	0.154	0.171	0.941	0.962
Elasticity	-1.381	-1.410	-1.473	-1.479	-1.395	-0.389	-0.439
Cohort Controls		X	X	X	X	X	X
Cohort-Specific Initial Conditions			X	X	X	X	X
Contemporary Controls				X	X	X	X
Year F.E.					X	X	
Reg F.E.						X	X
Country-Specific Time Trends							X

Notes: Sample consists of regions over time. Sample used to obtain mobility indexes excludes people with a migration background (i.e. also second generation migrants). Weights obtained using effective labour supply by age, retrieved from Mason et al. (2022). Cohort controls are average and coefficient of variation of years of education. Cohort-specific initial conditions include a summary indicator for historical precipitation, temperature, sea level pressure, relative humidity, wind speed, and global radiation associated with the respective cohorts, also weighted by cohort-participation weights. Contemporary controls include variables indicative of structural transformation and local development retrieved from Lehnert et al. (2023). Standard errors obtained by bootstrapping with 100 replications. *p<.1, **p<.05, ***p<.01. *Source*: see data section; own calculations.

APPENDIX C – Definitions

Figure C1. Modified Shapefiles to Include Non-EUROSTAT Regions

(a) Country



(b) NUTS 1

Source: European Commission – Eurostat/GISCO and ESRI. Country-level additions are illustrated in (a), based on modifications to the Eurostat/GISCO shapefile "NUTS_RG_01M_2016_4326_LEVL_0.shp", with administrative boundaries based on the 2016 version of NUTS and an 01M scale. In (b) the addition of Kosovo reshapes the bounds of the Serbian regions, based on modifications to NUTS_RG_01M_2016_4326_LEVL_1.shp. Modifications were conducted in ArcGIS Pro 3.02, using the "add join", "append", "merge", "export features" tools to extract and merge additional regions from the ESRI World Countries Generalized base map layer. Where boundaries were not perfectly aligned due to differences in scale, hierarchal preference were assigned to the 01M scale Eurostat/GISCO shapefiles.

Table C1. Modified ISCED Harmonization of ESS Education Measures from Waves 1-4 Excluded fr

ESS Definition	ESS-ISCED I less than lower secondary	ESS-ISCED II lower secondary	ESS-ISCED IIIb lower tier upper secondary	ESS-ISCED IIIa upper tier upper secondary	I adv
Bulgaria					
edlvbg	Not completed primary; Primary (I-IV grade)	Lower secondary (V-VIII grade)		Upper secondary (IX-XIII grade)	Post secon
Cyprus					
edlvcy	Not completed primary; Primary or first stage of basic	Lower secondary or second stage of basic		Upper secondary	Diploma
edlvacy	Not completed primary; Primary or first stage of basic	Lower secondary or second stage of basic		Upper secondary	Diploma
edlvfcy	Not completed primary; Primary or first stage of basic	Lower secondary or second stage of basic		Upper secondary	Diploma
edlvmcy	Not completed primary; Primary or first stage of basic	Lower secondary or second stage of basic		Upper secondary	Diploma
Estonia					
Edlvbee	Illiterate; Without education; Basic without professional qual; Primary without prof qual or uncomplete	Vocational education: less than 3 years; with 3 or more years; with acquisition of basic education	Vocational with acquisition of secondary; Vocational-secondary after acquisition of basic; Vocational secondary/technical school after basic	Secondary without professional qual; Vocational-seconadary after secondary; Vocational secondary/technical school after secondary	Vocational higher edu
edlvfee	Not completed primary; Primary	Basic		Secondary	Vocational
edlvmee	Not completed primary; Primary	Basic		Secondary	Vocational
France					
edlvfr	Sans diplôme; Non diplômés du CAP BEP filière professionnelle; Certificat d'études primaires	Non diplômés jusqu'à la fin 3ème, 2nde, 1ère filière general; CAP, examen de fin d'apprentissage artisanal; Brevet élementaire, brevet d'étude du premier cycle, brevet	BEP, BP, BEA, BEC, BEI, BES; Brevet de technicien, baccalauréat de technicien, baccalauré	Baccalauréat général, brevet supérieur	
Britain					
edlvgb	No qualifications	GCSE/O-level/CSE/NVQ1/NVQ2 or equiv		A-level/NVQ3 or equiv	NVQ4/N
edlvagb	No Qualifications	CSE Grade 2-5 / GCSE Grades D-G; CSE Grade 1/O-Level/GCSE Grades A-C		A-Level, As-Level Or Equiv	
edlvfgb	No qualifications	GCSE/O-level/CSE/NVQ1/NVQ2 or equiv		A-level/NVQ3 or equiv	NVQ4/N
edlvmgb	No qualifications	GCSE/O-level/CSE/NVQ1/NVQ2 or equiv		A-level/NVQ3 or equiv	NVQ4/N
Greece					
edlvgr	Illiterate/not completed primary; Primary	Partial secondary		Full secondary	Post secon
edlvagr	Analphabetic; Primary education	Lower secondary		Upper secondary	Post-comp
edlvfgr	Analphabetic; Primary education	Lower secondary		Upper secondary	Post-comp
edlvmgr	Analphabetic; Primary education	Lower secondary		Upper secondary	Post-comp
Ireland					
edlvie	None/primary not completed; Primary or equivalent	Intermediate/junior/group cert or equiv		Leaving cert or equiv	Diploma/
edlvaie	None/primary not completed; Primary or equivalent	Intermediate/junior/group cert or equiv		Leaving cert or equiv	Diploma/
edlvbie	None/primary not completed; Primary or equivalent	Intermediate/junior/group cert or equiv		Leaving cert or equiv	Diploma o
edlvfie	None/primary not completed; Primary or equivalent	Intermediate/junior/group cert or equiv		Leaving cert or equiv	Diploma o
edlvmie	None/primary not completed; Primary or equivalent	Intermediate/junior/group cert or equiv		Leaving cert or equiv	Diploma o
Italy					
edlvit	Senza titolo; Licenza elementare	Licenza media / avviamento professional		Diploma scuola media superiore	
Portugal					
edlvpt	Nenhum; 1 ciclo; 2 ciclo	3 ciclo		Secundario	Superior P
edlvapt	Nenhum; 1 ciclo; 2 ciclo	3 ciclo		Secundario	Superior P
Sweden					
edlvse	Not finished elementary; Elementary, old; Elementary	Lower secondary and elementary; Vocational school 1963-1970; 2 year high school	Vocational high school after 1992	3-4 year high school prior 1995; Theoretical high school after 1992; entered University, no exam	University
edlvase	Ej avslutad folkskola/grundskola; Folkskola; Grundskola/Enhetsskola	Realskola/Flickskola; Fackskola (1963-1970); 2-årig gymnasielinje, 2-årig yrkesskola	Yrkesinriktat gymnasium (efter 1992)	3- eller 4 årig gymnasium (före 1995); Teoretiskt gymnasium (efter 1992); Universitet/högskola utan examen	Universite
edlvfse	Ej avslutad folkskola/grundskola; Folkskola; Grundskola/Enhetsskola	Realskola/Flickskola; Fackskola (1963-1970); 2-årig gymnasielinje, 2-årig yrkesskola	Yrkesinriktat gymnasium (efter 1992)	3- eller 4 årig gymnasium (före 1995); Teoretiskt gymnasium (efter 1992); Universitet/högskola utan examen	Universite
edlvmse	Ej avslutad folkskola/grundskola; Folkskola; Grundskola/Enhetsskola	Realskola/Flickskola; Fackskola (1963-1970); 2-årig gymnasielinje, 2-årig yrkesskola	Yrkesinriktat gymnasium (efter 1992)	3- eller 4 årig gymnasium (före 1995); Teoretiskt gymnasium (efter 1992); Universitet/högskola utan examen	Universite
Turkey					
edulvla	Less than lower secondary education	Lower secondary education completed		Upper secondary education completed	
edlvtr	Okuma-yazma bilmiyor; Okuma-yazma biliyor ama okul bitirmemis/diplomasiz; Ilkokul mezunu (5 yil); Ilkögretim mezunu (8 yil)	Genel ortaokul mezunu; Mesleki ortaokul mezunu	Mesleki lise mezunu	Genel lise mezunu	
edulvlfa	Less than lower secondary education	Lower secondary education completed		Upper secondary education completed	
edlvftr	Okuma-yazma bilmiyor; Okuma-yazma biliyor ama okul bitirmemis/diplomasiz; Ilkokul mezunu (5 yil); Ilkögretim mezunu (8 yil)	Genel ortaokul mezunu; Mesleki ortaokul mezunu	Mesleki lise mezunu	Genel lise mezunu	
edulvlma	Less than lower secondary education	Lower secondary education completed		Upper secondary education completed	
edlvmtr	Okuma-yazma bilmiyor; Okuma-yazma biliyor ama okul bitirmemis/diplomasiz; Ilkokul mezunu (5 yil); Ilkögretim mezunu (8 yil)	Genel ortaokul mezunu; Mesleki ortaokul mezunu	Mesleki lise mezunu	Genel lise mezunu	
Ukraine					
edlvua	Not completed primary; Primary (4-7 years of secondary)	Not completed secondary (8-9 years of secondary)		Completed secondary (10-11 years of secondary)	Secondary more than

Table C2. Standardized Years of Schooling by Modified-ISCED Educational Rank

Modified ISCED Definition		Standardized Years of Schooling Assigned
ESS-ISCED I	less than lower secondary	6
ESS-ISCED II	lower secondary	9
ESS-ISCED IIIb	lower tier upper secondary	11
ESS-ISCED IIIa	upper tier upper secondary	12
ESS-ISCED IV	advanced vocational	13
ESS-ISCED V1	lower tertiary education	15
ESS-ISCED V2	higher tertiary education	17

APPENDIX D – Weighting Procedure

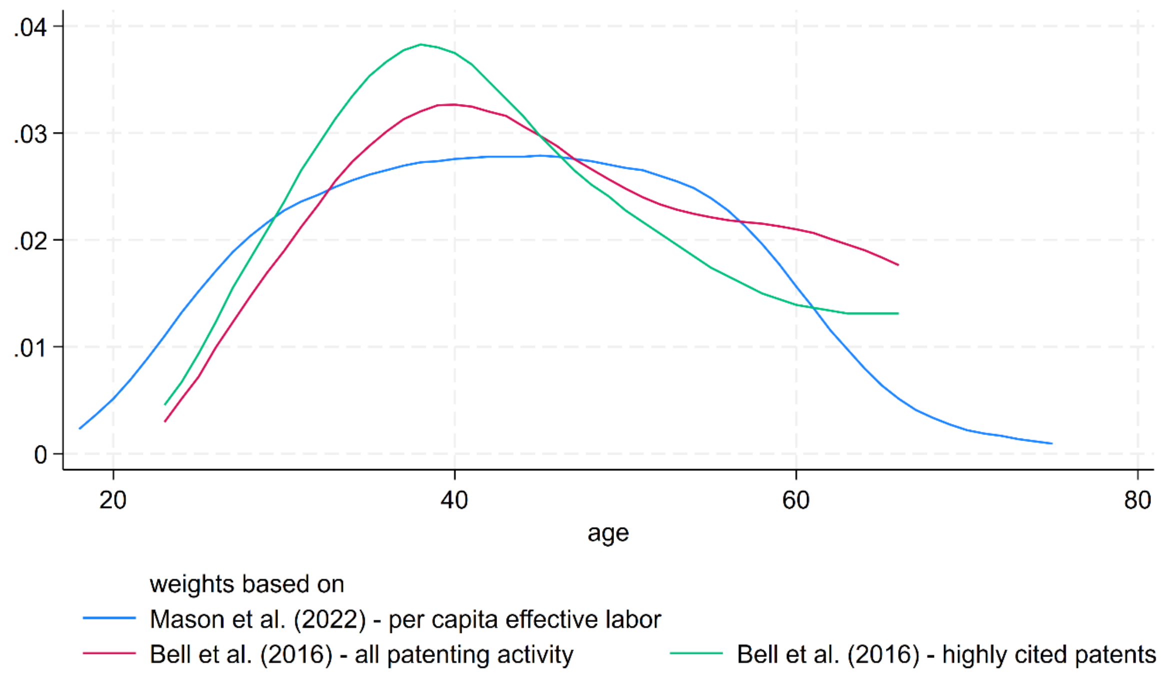
To link social mobility and economic development, cohort-specific mobility measures are transformed into time-series measures, where the index value of a given cohort is weighted by the expected contribution of cohort members to the economy in a given year (following Neidhöfer et al., 2023):

$$M_{rt} = \sum_{c=1}^{C} w_{ct} m_{crt} \qquad (3)$$

where the mobility index M in region r for each year t is the weighted average mobility of people born in cohort 1940-59 (c = 1), 1960-79 (c = 2), or 1980-99 (c = 3): i.e. the sum of the mobility of each cohort (m) multiplied by the respective cohort-participation weight (w). Hereby, the three weights sum up to one for each year.

We apply two different weighting procedures. The first is based on per-capita effective labour profiles over the life-cycle retrieved from Mason et al. (2022), where w_{ct} is the share of the cohort's effective labour over the total effective labour supply in a given year. The second is based on innovation life-cycle profiles for all patenting activity and highly cited patents, both derived from Bell et al. (2016). Figure D1 shows the age-participation profiles used to apply the aforementioned procedures.

Figure D1. Age-participation profiles used to obtain the country-cohort weights



After computing the relative contribution by age as an integral fraction of the respective participation profile, absolute cohort weights at time t are computed by cohort as a sum of the contribution of the in-range ages in year t (e.g. in t = 2007, the oldest members of c = 1 are no longer in range). Relative cohort weights are computed as the share of the cohort weight in t over the sum of cohort weights in t yielding w_{ct}. Figure D2 shows the respective weights for each cohort in every year.

Figure D2. Annual Cohort Weights