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Economic complexity thrives with academic freedom

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Abstract
Academic freedom allows the development of new and revolutionary ideas, which are expected to lead to innovation and the creation of diverse, unique and complex products. This study explores that relationship empirically and finds that academic freedom boosts not only economic complexity but also technological and research complexity. Hence, academic freedom is fundamental to enhance the development of a country's productive capacity.

Keywords: academic freedom, economic complexity, technology, research
JEL Classification Codes: A13, I25, O11, O30

1. Introduction

The capacity of a country to produce and export a diverse range of sophisticated and high-productivity products is defined in the literature as economic complexity (Hidalgo and Hausmann, 2009). This is an indicator of the formal and tacit knowledge present in a country which is expressed in the range of diversified products it makes. There are several factors that can drive economic complexity, from economic – such as level of income and education – to institutional (for a review, see: Nguyen et al., 2020; Hidalgo, 2021; Vu, 2022). However, the potential role of academic freedom in shaping a country's level of economic complexity has been overlooked. Theoretically, academic freedom can play a crucial role in fostering economic complexity by enabling the development and application of diverse knowledge, technologies, and innovations. As economic complexity requires advanced capabilities driven by innovation, collaboration, and problem-solving, it can thrive in an environment of academic freedom.

Academic freedom allows researchers and universities to explore ideas without external

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constraints, fostering creativity and the generation of new knowledge. This openness often stimulates entrepreneurs to make use of the new knowledge produced in academia in innovative activities, benefiting productivity growth (Berggren and Bjørnskov, 2022) and the development of skilled human capital that drive industries toward producing complex, value-added goods and services. Hausmann et al. (2007, 2014) highlight the importance of knowledge networks in driving productive capabilities. These networks are nurtured in environments where academic freedom flourishes, as unrestricted inquiry allows for the cross-pollination of ideas between academic, industrial, and governmental sectors.

Countries with greater academic freedom – often strengthened by democratization – attract and retain highly skilled individuals, thereby enhancing human capital accumulation. Recent evidence shows that the shift from autocracy to democracy significantly increases the impact of research in social sciences and humanities by removing political restrictions on scholars (Tayebi and Teimouri, 2025). Bjørnskov and Méon (2015) link such institutional freedom to superior economic performance. This enriched human capital, in turn, supports the diversification of industries into higher-value-added sectors, as reflected in greater economic complexity. Leetaru and Lami (2022) observe that nations with vibrant, unrestricted academic ecosystems consistently excel in global innovation rankings, further fostering economic sophistication and long-run growth.

Additionally, academic freedom facilitates interdisciplinary collaboration, essential for addressing multifaceted challenges in production and technology. This is particularly relevant for developing economies, where complex industries rely on knowledge-sharing platforms. Conversely, constraints on academic inquiry stifle innovation, limiting countries' ability to transition to more complex economies.

Using data for a panel of 139 countries over the period 1998-2022, this study provides sound evidence that academic freedom is positively associated not only with economic complexity, but also with technology complexity and – to a greater degree – research complexity. Hence, this paper contributes to our knowledge by establishing academic freedom as a fundamental determinant of economic complexity and consequently long-run economic performance and economic development.

The rest of the paper is organized as follows. Section 2 describes the data and methodology. The empirical analysis and discussion of results are presented in Section 3. Finally, Section 4 concludes.

2. Data and methods

For this analysis, we compile data from 139 countries over the period 1998-2022. This selection is determined by data availability for the dependent variable, which is defined by the Economic Complexity Index (ECI) developed by Hidalgo and Hausmann (2009) and available from the Observatory of Economic Complexity (OEC). This measure relies on trade data, i.e. on information about the sophistication of the productive activities and products that is implicit in their geographic distribution. Therefore, the ECI provides an internationally comparable measure of productive knowledge based on the sophistication of the types of products produced and exported by a country. Hidalgo and Hausmann (2009) use the method of reflections to capture the availability of productive expertise and knowledge within a country. They rely on two metrics: diversity and ubiquity. A country that produces and exports a diverse range (number) of products with revealed comparative advantage has a higher level of diversity. As ubiquity relates to the number of countries exporting a specific product with a revealed comparative advantage, then a country producing and exporting less ubiquitous products should be a country with greater productive expertise and knowledge. Hence, high diversity and low ubiquity indicate greater productive knowledge and economic complexity.

While most of the studies on economic complexity rely on the metrics developed by Hidalgo and Hausmann (2009), which are based on trade data – i.e. on the diversity of exports a country produces and their ubiquity/number of the countries able to produce them – that measure misses information about innovative activities, such as patent applications and research publications (Stojkoski et al., 2023). These can also be influenced by the level of academic freedom. As in Stojkoski et al. (2023), the issue that we try to address here is that trade-based metrics of complexity may underestimate the complexity of economies that are distant from global markets (e.g: Australia, New Zealand, South Africa, Chile). Their economic complexity might be better expressed in their capacity to produce scientific research and technological innovations than sophisticated exports. Therefore, we also follow this multidimensional approach by exploring how academic freedom affects technology complexity (TechCI) and research complexity (ResCI). Both are computed based on the ECI method developed by Hidalgo and Hausmann (2009), but TechCI relies on patent applications data from World Intellectual Property Organization's International Patent System and TechCI is obtained using published documents data from SCImago Journal and Country Rank portal. As for ECI, the data for these additional indices were obtained from the OEC.

To measure the level of academic freedom, we use the Academic Freedom Index (AFI) available from the Varieties of Democracy (V-Dem) Project.[1] To compute this index, V-Dem relies on set of indicators – that we will also employ in this study – such as: freedom of academic exchange and dissemination (AFexch); freedom to research, teach and discuss ideas (AFres); higher-education institutional autonomy (AFaut); campus integrity or freedom from institutional censorship (AFint); and freedom of academic and cultural expression (AFexpr).[2] For the reasons discussed above, we expect that academic freedom promotes more economic complexity. In fact, looking at Figure 1 – where the unconditional correlation between ECI and AFI is illustrated using country averages over the period 1998-2022 – we get a glimpse of that anticipated association. The challenge now is to test whether this relationship remains valid

[1] That index varies between 0 and 1 and it is labelled in the V-Dem dataset as v2xca_academ.

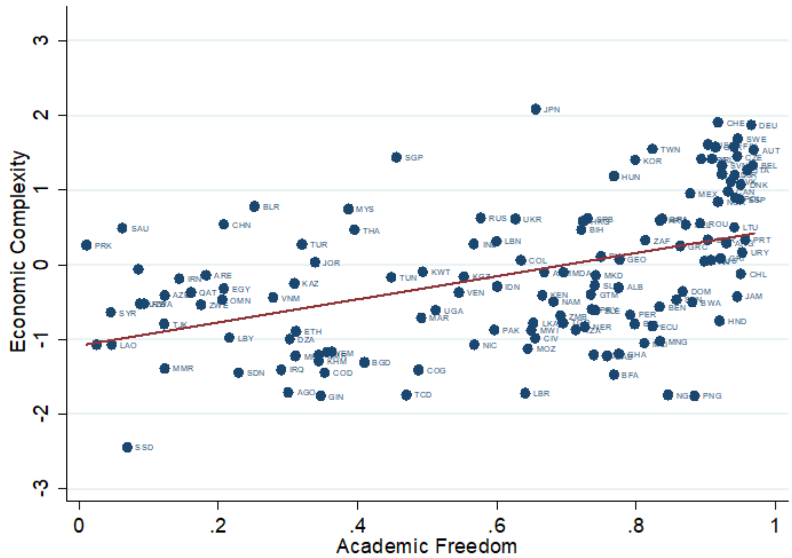
[2] These variables are labelled in the V-Dem dataset, respectively, as v2cafexch, v2cafres, v2cainsaut, v2casurv, and v2clacfree. As they are not indices, they were normalised to the interval 0-1 using the formula Xnorm=(X-min(X))/(max(X)-min(X)) to make them comparable with the aggregate index AFI.

when we control for other drivers of economic complexity. For that we need to rely on relevant control variables and suitable econometric techniques.

The selection of the control variables follows the literature on economic complexity (see, among others: Hausmann et al., 2007; Hidalgo and Hausmann 2009; Hidalgo and Hausmann 2011; Hausmann et al., 2014; Nguyen et al., 2020; Vu, 2022):

- The level of income, measured by the logarithm of real GDP per capita (RealGDPpc), considered to be a vital booster of economic complexity (Hidalgo and Hausmann, 2009).
- Gross capital formation as percentage of GDP (CapitalFormation).
- Labour force participation rate as percentage of the total population aged 15-64 (LabourForce).

Figure 1. Relationship between academic freedom and economic complexity



Notes: Unconditional correlation between the Academic Freedom Index and Economic Complexity Index. Averages per country over the period for which data are available for each variable. The abbreviations for each country follow the ones in the World Development Indicators. The straight line corresponds to the fitted values.

- Trade openness (TradeOpenness), i.e. exports plus imports over GDP (in percentage).
- Average number of years in school (Education) retrieved from the United Nations' Human Development Indicators (UN-HDI). By enhancing human capital, education is considered another building block of economic complexity. (Hausmann et al., 2007, 2014; Hausmann and Hidalgo, 2011).
- Dummy variable that takes the value of 1 if the country is considered a democracy (Democracy), i.e. if the autocracy-democracy index polity2 from the Polity V Project database is equal or higher than 6; 0 otherwise.
- Logarithm of population density (PopDens), measured in logs of people per square kilometre of land area. This is a proxy for the dimension of the internal market as a

potential booster for products diversity and complexity.

- Logarithm of the land area (Area), measured in logs of square kilometres. This accounts for the role of geographic diversity foster the development of different products.

In line with the literature, we expect that these factors have a positive impact on ECI. The data for these control variables were obtained from the World Bank's World Development Indicators (WDI), except for Education and Democracy.[3]

The panel data specification to be estimated is defined as follows:[4]

$$ECI_{it} = \alpha + \beta AFI_{it} + \gamma X_{it} + \delta DC_i + \tau_t + u_{it} \tag{1}$$

where α is the constant term, β is the coefficient on AFI (or one of its components), $\boldsymbol{\gamma}$ represents the vector of parameters for the set of control variables $\boldsymbol{X}$ for each individual/country i and time t, $\boldsymbol{\delta}$ is the vector of parameters on the dummies for continents ($\boldsymbol{DC}$),[5] τ represents the (year) time effects, and u_{it} is the usual white-noise error term. The model is estimated using a Panel Corrected Standard Error (PCSE) estimator given the presence of cross-sectional dependence.[6]

3. Results

The empirical results are reported in Table 1, where the PCSE estimations consider a panel-specific AR1 structure to deal with serial autocorrelation,[7] while they simultaneously control

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[3] Some supplementary material can be found in the Appendix to this paper. In particular, Table 2 provides descriptive statistics for the variables used in this study and a list with the countries considered.

[4] All the variables considered in this analysis have stationary properties, which have been confirmed by panel unit root tests (see Table 3 in the Appendix).

[5] Continent dummies are used to account for countries' heterogeneity as *ECI* does not vary much among countries in the same continent. In addition, this is a parsimonious way of addressing potential heterogeneity which avoids a potential loss of efficiency in estimator used.

[6] The nestedness of the economic systems (and products) among countries (Hidalgo and Hausmann, 2009; Hausmann et al., 2014) leads to a potential correlation across panels. Cross-sectional dependence tests confirmed that all variables – as well as the residuals from the pooled regression of *ECI* on *AFI* and the control variables – have cross-sectional dependences (see Table 4 in the Appendix). Wooldridge test for autocorrelation in panel data also shows the presence of serial correlation (i.e. the null of no first-order autocorrelation is rejected: test-statistic = 78.5; p-value = 0.000). Hence, the PCSE estimator proposed by Beck and Katz (1995) arises as the most appropriate technique to deal with both cross-sectional dependence and serial correlation (see also Nguyen et al., 2020).

[7] In this panel-specific AR1 structure the autocorrelation parameter is assumed to be different for each panel. Alternatively, we could assume a common parameter for all panels. While controlling for panel-specific serial correlation may lead to less precise estimates of variability (especially if *T* is low, which is not the case here), allowing for variation among the autocorrelation parameters can improve the overall estimation performance and accuracy (Beck and Katz, 1995). Nevertheless, assuming a common AR1 serial correlation renders similar results. Those results are not reported here, but they are available upon request.

for heteroscedasticity and cross-sectional dependence across panels. The results are provided first for the full sample and then for a sample excluding single-party countries to ensure that the respective results are not driven by any of them.

The estimations show that academic freedom has a significant positive impact on economic complexity. In statistical terms, when AFI increases by one unit, ECI rises by about 0.61 units (see column 1). The results also show that academic freedom helps to promote technology (TechEC) and research (ResEC) complexity. The magnitude of the impact is substantially higher in what regards to research complexity. Similar results are obtained for the components of AFI (see Figure 2 in the Appendix).[8] Moreover, the additional results in Table 1 (columns 3-6) also show that our findings are not driven by single-party countries.

In economic terms, the evidence provided by this study implies that countries with more academic freedom present a fertile ground for creativity and to develop new ideas and more complex products. This spirit towards innovation, supported by strong institutions, leads to a higher accumulation of productive capabilities that ultimately translate into higher levels of economic complexity (Vu, 2022). By valuing academic freedom, they also tend to invest more in human capital enhancing the skill development that supports complex industries (Hausmann and Hidalgo, 2011). Academic freedom can also attract high skilled workers, promoting cultural diversity, enhancing knowledge exchange and innovation through cross-pollination of ideas. All this contributes further to the development of complex economies and technologies.

In line with the literature, the results also confirm the relevance of the control variables in driving economic complexity. In particular, countries with a higher real GDP per capita, more labour force, more open to trade, more educated citizens, a strong democratic environment, densely populated areas and a substantial dimension (large i.e. large internal markets and geographical diversity) are associated with higher levels of economic complexity.

4. Concluding remarks

By addressing a dimension not yet explored in the literature, this study unveils an important link between academic freedom and economic complexity. Using data for a panel of 139 countries over the period 1998-2022, this study proves the existence of a strong positive link between academic freedom and economic complexity, which also translates to technology and research complexity. A country that promotes academic freedom offers the necessary environment for creative research and innovation to thrive leading to the development of a diverse range of complex and high-productivity products. Ultimately, this puts the country in a

[8] The coefficient on freedom of academic exchange and dissemination (*AFExch*) provides the highest magnitude for that impact on ECI. In what regards to *ResEC*, we do observe an almost one to one impact from components of academic freedom such as freedom of academic exchange and dissemination, freedom to research and teach, and institutional autonomy. These results show that more than boosting economic complexity, academic freedoms are essential for the development of complex research and the respective dissemination. The results for the control variables are consistent with the ones reported in Table 1 and are available upon request.

trajectory of economic growth and development.

Table 1. Estimation results

Dep.Var.:	Full sample			Excluding single-party countries		
	ECI **(1)**	***TechCI*** **(2)**	***ResCI*** **(3)**	***ECI*** **(4)**	***TechCI*** **(5)**	***ResCI*** **(6)**
AFI	0.6148***	0.3713***	0.7532***	0.6784***	0.3594***	0.7410***
	(0.0769)	(0.0976)	(0.1192)	(0.0779)	(0.1020)	(0.1451)
LnRealGDPpc	0.3355***	0.3634***	0.4352***	0.3293***	0.3196***	0.4440***
	(0.0155)	(0.0241)	(0.0494)	(0.0150)	(0.0254)	(0.0488)
CapitalFormation	0.0007	-0.0013	0.0056***	0.0005	-0.0037	0.0048**
	(0.0013)	(0.0025)	(0.0021)	(0.0013)	(0.0026)	(0.0022)
LabourForce	0.0035**	-0.0007	0.0131***	0.0028*	-0.0023	0.0137***
	(0.0014)	(0.0023)	(0.0044)	(0.0016)	(0.0024)	(0.0047)
TradeOpenness	0.0010***	0.0022***	0.0007**	0.0012***	0.0019***	0.0007**
	(0.0004)	(0.0006)	(0.0003)	(0.0004)	(0.0006)	(0.0003)
Education	0.0875***	0.1233***	0.1140***	0.0893***	0.1354***	0.1161***
	(0.0077)	(0.0111)	(0.0163)	(0.0075)	(0.0141)	(0.0198)
Democracy	0.0801***	0.1585***	0.1353***	0.0741**	0.1585***	0.1303***
	(0.0304)	(0.0605)	(0.0442)	(0.0305)	(0.0608)	(0.0446)
LnPopDens	0.2717***	0.4004***	0.2225***	0.2699***	0.3763***	0.2364***
	(0.0181)	(0.0303)	(0.0429)	(0.0176)	(0.0360)	(0.0441)
LnArea	0.1515***	0.3722***	0.2042***	0.1531***	0.3335***	0.2240***
	(0.0109)	(0.0200)	(0.0336)	(0.0111)	(0.0240)	(0.0321)
Observations	2593	1882	2388	2519	1829	2316
Countries	128	104	123	124	100	119
R-squared	0.790	0.657	0.755	0.789	0.612	0.729

Notes: Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Continent dummies included for Africa, Asia, Europe, North America and South America (Oceania is the base category). Times dummies and a constant were also included in all the regressions but omitted here for brevity. All regressors except Democracy, LnPopDens and LnArea are lagged one period. PCSE estimations consider a panel-specific AR1 structure (i.e. the autocorrelation parameter is assumed to be different for each panel) to deal with serial autocorrelation, while simultaneously controlling for heteroscedasticity and cross-sectional dependence across panels. Single-party countries: Cambodia, China, Cuba, Laos, North Korea, Syria, Vietnam.

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Appendix

Table 2. Descriptive statistics, 1998-2022

	Obs.	Mean	Std. Dev.	Min.	Max.
ECI	2972	0.000	0.996	-3.378	2.283
TechCI	1970	0.066	0.992	-3.008	1.599
ResCI	2560	0.077	0.995	-2.730	2.885
AFI	2972	0.649	0.299	0.009	0.981
AFexch	2795	0.649	0.214	0.009	0.978
AFres	2795	0.630	0.213	0.044	0.987
AFaut	2970	0.601	0.214	0.014	0.976
AFint	2970	0.627	0.211	0.102	0.983
AFexpr	2796	0.628	0.217	0.010	0.980
RealGDPpc	2770	14195.95	17871.87	344.88	88588.48
CapitalFormation	2671	24.361	7.344	1.525	79.401
LabourForce	2815	67.319	10.385	37.960	89.650
TradeOpenness	2714	82.578	51.024	0.785	442.62
Education	2792	8.615	3.036	0.975	14.132
Democracy	2810	0.598	0.490	0	1
PopDens	2803	227.74	890.44	1.665	7965.88
Area	2815	1010054.0	2279634.0	670.00	16400000.0

Notes: Descriptive statistics for the 139 countries, for which ECI data are available, across the 1998-2022 period. List of countries: Afghanistan, Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, Bangladesh, Belarus, Belgium, Benin, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Cambodia, Cameroon, Canada, Chad, Chile, China, Colombia, Democratic Republic of Congo, Republic of Congo, Costa Rica, Cote d'Ivoire, Croatia, Cuba, Czechia, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Finland, France, Gabon, Georgia, Germany, Ghana, Greece, Guatemala, Guinea, Honduras, Hong Kong, Hungary, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, North Korea, South Korea, Kuwait, Kyrgyz Republic, Laos, Lebanon, Liberia, Libya, Lithuania, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mexico, Moldova, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, North Macedonia, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russia, Rwanda, Saudi Arabia, Senegal, Serbia, Sierra Leone, Singapore, Slovak Republic, Slovenia, South Africa, South Sudan, Spain, Sri Lanka, Sudan, Sweden, Switzerland, Syria, Taiwan, Tajikistan, Tanzania, Thailand, Togo, Tunisia, Türkiye, Turkmenistan, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela, Vietnam, Yemen, Zambia, Zimbabwe.

Table 3. Panel unit root tests

	ADF Fisher-type tests			
	P	*Z*	*L**	*Pm*
ECI	931.57 (0.000)	-19.74 (0.000)	-21.59 (0.000)	29.25 (0.000)
TechCI	702.99 (0.000)	-17.71 (0.000)	-19.20 (0.000)	26.08 (0.000)
ResCI	784.66 (0.000)	-18.19 (0.000)	-18.73 (0.000)	24.10 (0.000)
AFI	1201.5 (0.000)	-16.63 (0.000)	-18.81 (0.000)	32.18 (0.000)
AFexch	966.00 (0.000)	-17.10 (0.000)	-20.12 (0.000)	29.37 (0.000)
AFres	1124.7 (0.000)	-18.78 (0.000)	-24.15 (0.000)	35.69 (0.000)
AFaut	1136.6 (0.000)	-17.82 (0.000)	-21.25 (0.000)	31.40 (0.000)
AFint	1078.9 (0.000)	-18.14 (0.000)	-20.40 (0.000)	30.52 (0.000)
AFexpr	1157.3 (0.000)	-19.02 (0.000)	-22.88 (0.000)	32.91 (0.000)
LnRealGDPpc	1301.5 (0.000)	-20.50 (0.000)	-23.07 (0.000)	32.48 (0.000)
CapitalFormation	1627.7 (0.000)	-29.09 (0.000)	-33.05 (0.000)	47.45 (0.000)
LabourForce	956.37 (0.000)	-16.99 (0.000)	-17.67 (0.000)	21.95 (0.000)
TradeOpenness	1310.5 (0.000)	-23.53 (0.000)	-25.76 (0.000)	34.74 (0.000)
Education	1134.6 (0.000)	-19.90 (0.000)	-21.35 (0.000)	28.26 (0.000)
LnPopDens	1522.3 (0.000)	-24.67 (0.000)	-28.51 (0.000)	40.02 (0.000)
LnArea	265.84 (0.000)	-5.036 (0.000)	-5.166 (0.000)	7.873 (0.000)

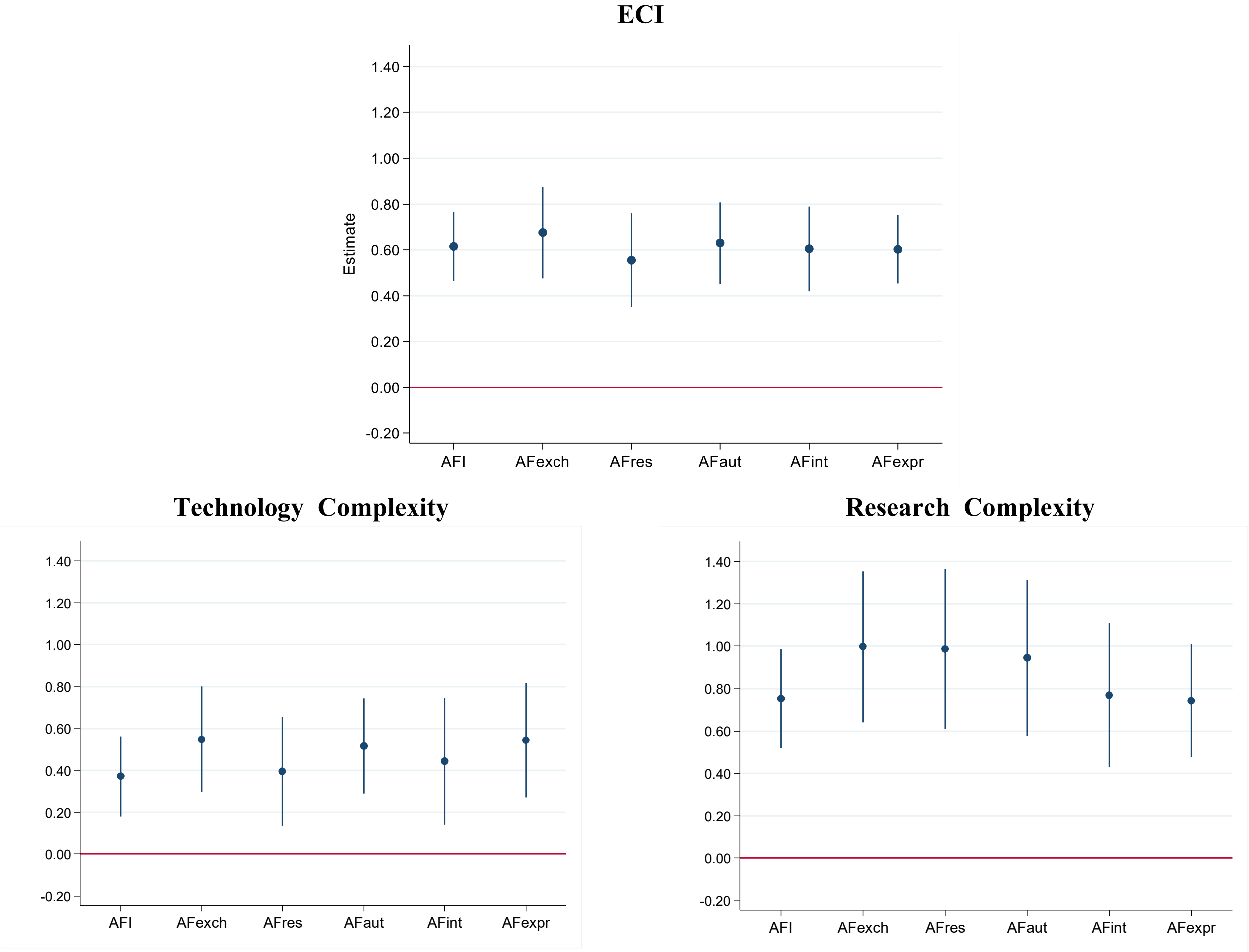
Notes: Four Fisher-type ADF unit-root test statistics are reported: inverse chi-squared P; inverse normal Z; inverse logit L*; and the modified inverse chi-squared Pm. One lag of the series is used in the ADF regressions, but different lag structures produced similar results. Phillips-Perron unit-root tests were also considered, but the conclusions remained unchanged (those results are not reported here but are available upon request). These tests are preferred due to the fact of the panel is not strongly balanced.

Table 4. Cross-sectional dependence tests

	Pesaran	Fan et al.	Pesaran & Xie	Juodis & Reese
ECI	2.69 (0.007)	31776.24 (0.000)	-2.47 (0.013)	-2.54 (0.011)
AFI	561.39 (0.000)	81175.24 (0.000)	9.62 (0.000)	-3.02 (0.000)
LnRealGDPpc	530.40 (0.000)	76669.96 (0.000)	42.94 (0.000)	-2.14 (0.032)
CapitalFormation	265.82 (0.000)	40102.71 (0.000)	529.70 (0.000)	1.91 (0.056)
LabourForce	643.25 (0.000)	93011.79 (0.000)	-2.25 (0.024)	-3.55 (0.000)
TradeOpenness	367.31 (0.000)	53818.53 (0.000)	331.77 (0.000)	-2.04 (0.041)
Education	607.45 (0.000)	87835.37 (0.000)	8.70 (0.000)	-3.21 (0.001)
Democracy	103.54 (0.000)	18186.44 (0.000)	-4.08 (0.000)	-2.40 (0.016)
LnPopDens	763.26 (0.000)	109374.10 (0.000)	-3.09 (0.002)	-2.27 (0.023)
LnArea	1026.05 (0.000)	150973.02 (0.000)	1.82 (0.069)	-5.08 (0.000)
Residuals	-2.16 (0.031)	19681.72 (0.000)	-3.12 (0.002)	-2.07 (0.038)

Notes: See xtcd2 command for Stata and references for the respective tests therein. Under the null hypothesis there is weak or no cross-sectional dependence; under the alternative, there is strong cross-sectional dependence. Residuals correspond to the residuals from the model with AFI.

Figure 2. Impact of academic freedoms on economic, technology and research complexity



Notes: See Table 1. The dependent variables are ECI, Technology Complexity Index and Research Complexity Index, respectively. Only the estimates and the 95% confidence intervals for the academic freedom variables are reported. The estimated specifications include the same control variables as the ones reported in Table 1.