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Testing for Convergence Innovation and Club Clustering in Selected Economies 1995-2017

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Abstract
Innovation convergence is a deterministic process resulting from the change in micro and macro innovation determinants. It is characterized by firms' search for innovative opportunities in other economic sectors and in their development from mining through heavy industry to material processing sector, discovering new technologies that connect individual products to a more integrated global system, diversifying, ensuring technical scope growth, and start-ups contributing to new managerial leadership. The aim of this study is to contribute to our knowledge of convergence innovation by providing empirical evidence on it. To this purpose, we use a nonlinear time-varying factor model to test for convergence innovation and countries' club clustering. For the sample of 29 countries from 1995 to 2017, we identify two significant convergence clubs and one divergent group (Cyprus, Czech Republic, and The Netherlands). The empirical evidence indicates that innovation singularity could appear as a significant barrier and limiting factors for firms' and countries' growth in the future. Design and new product development trends in these countries follow a different decoupling path from the rest of the sample. Policymakers and practitioners should carefully evaluate innovation determinants and constraints (decoupling drivers) in setting up innovation policies on a micro and macro level.

Keywords
Innovation convergence, Convergence test, Innovation policies, Nonlinear time-varying factor model, Globalization and innovation

Introduction

Convergence innovation constitutes a new domain with largely unstudied potential in economics and management. So far, the research on this topic focuses on various aspects, like a convergence of science and technology Lee et al. (2018). Convergence innovation is a relatively young field of research. Most previous research focused on technological advancements and industrial changes in developed countries. Convergence-oriented innovations were the exception, not the rule. Researchers have not done enough empirical research on convergence to date, and as such, we do not have much understanding of the concept or hypothesis. This gap in the existing literature is a motivation to conduct further research on the subject, Lee (2016).

Our study is a seminal work in the field of convergence innovation, as it provides empirical results to support the convergence hypothesis using innovation data from Stehrer et al. (2019). To this purpose, we use a nonlinear time-varying factor model following Phillips and Sul (2007b, a, 2009) and Du (2017); Sichera and Pizzuto (2019) to test for convergence innovation and countries' club clustering.

Convergence innovation is an extended phenomenon. Schumpeter's prediction of new innovations emerging due to large-scale research and development projects funded by corporations is widespread. Convergence innovation is a by-product of several convergence processes (Owen et al., 2018; Rizos et al., 2016). The first one is technological convergence. Rosenberg (1963, 1983) documented the late-20th-century convergence. He found that closely related technical problems were solved across various machine types. He referred to this phenomenon as' technological convergence' by Song et al. (2017), Boussemart et al. (2020), Jeong and Lee (2015), Kim and Lee (2020), Lim et al. (2018).

Scientific knowledge convergence is the second source of convergence innovation. The previous study shows that greater scientific capacity promotes better integration of converging scientific and technological knowledge, which means the more likely science will be in the research and development process, claims innovation, and claims research (Lan et al., 2022). This is, of course, crucial to improving the quality of the organization Lee et al. (2018), Kodama et al. (2016), Zhou et al. (2019), Kodama and Kimura (2020), Simeth and Raffo (2013). The idea is to combine digital technologies, creativity, design knowledge, and art knowledge to create more agile and competitive firms (Cetindamar and Babak, 2020). The formal is crucial for growth on the micro and macro level (Yun and Kim, 2016; López-Cabarcos et al., 2020). This is a developing area of research. The aim of this article is to contribute to our knowledge of convergence innovation by providing empirical evidence on it.

The available data is limited, and no previous study focused on providing empirical evidence to sustain the convergence innovation hypothesis. Our research focuses on the more difficult problem of providing empirical evidence on convergence innovation. This is the missing link in the literature on convergence innovation. Convergence innovation was widely discussed in theoretical, meta-analysis, or surveys (limited data). The intention of this research is to provide reliable data evidence and determine convergence clubs. A novel aspect of this research is to apply state-of-the-art econometric modelling to check for convergence innovation.

The core objective of the present investigation is to check for the existence of convergence innovation on an empirical level. A secondary objective of this study is to determine convergence clubs and analyze the relative transition path (country and club level). Finally, this study also tests for innovation divergence as an exception from the convergence innovation hypothesis.

For convergence testing, we use data from 29 countries from 1995 to 2017. Data selection is directly related to data availability since convergence testing requires strongly balanced panel data, so countries without needed data were excluded from the analysis. We use industry-level data from Stehrer et al. (2019) on intangible assets with design and other product developments as proxy variables for convergence innovation. Convergence innovation reflects firm-level data (gross fixed capital formation, current prices, national currency, millions in logarithm) on the innovative property, including research and development, mineral exploitation, artistic originals, and design as defined in Stehrer et al. (2019). To test for convergence innovation, we use a nonlinear time-varying factor model following Phillips and Sul (2007b, a, 2009); Du (2017); Sichera and Pizzuto (2019).

The paper is organized as follows: the first part introduces the background and importance of studying convergence innovation. The second part discusses the definition, previous studies, and research gaps in the literature on convergence innovation. This is followed by section three, which sets up the data and methods we use in the study to search for empirical evidence in convergence innovation. The following section considers the main findings and results of our empirical study. Section five includes a discussion about robustness results, linking the results with previous study findings. The main conclusions of this work are drawn together and presented in conclusion.

Theoretical background

In this section, we review the related literature on convergence innovation. Studies on convergence innovation are lacking in the primary literature on innovation management. Here we review the contributions related to the topic.

Convergence innovation starts with research on technology and industry convergence, Rosenberg (1963). Diverse technologies merge or become more integrated at different speeds. Manufacturing companies in the East are at the forefront of new industrial revolutions. Several technologies are expected to integrate to the point where they will use each other and produce the latest technologies and products in the future. More companies than ever develop new products through convergence, driving the fourth industrial revolution. Such processes, directly and indirectly, lead to convergence innovation, leaving an extensive research gap in the literature.

Pioneering work of Kodama (1986, 1991, 1993), Kodama et al. (2016), and Rosenberg (1963, 1983) on technological and knowledge convergence point to understanding the dynamics of convergence as crucial to managing the results of the process. It is possible to compare the properties of convergence before and after the episode of formalization. The convergence is likely to change the characteristics of innovation. Furthermore, the technical elements' characteristics may differ after convergence, as some technical products are chemically mixed. Convergence can reduce costs in the short run, but it can make things more difficult in the long run, or it can only lock in another generation. Similarly, convergence processes could reveal a creative or provocative feature in the finished product Lee (2016).

Despite insufficient research on convergence processes, Kim et al. (2014) argue they are disequilibrated between "reference technologies" and "matching technologies." The two types of convergence technologies tend to innovate at different speeds, which requires continuous development to maintain an ideal balance between reference technology and matching technology. Lee et al. (2015) studied convergence innovation in the textile machinery industry in Korea. This paper aims to identify the causes and constellations that have led to the decline in Korean equipment and methods in the textile industry. Employment data were studied as an index of economic factors, while patents were studied as an index of convergence activities.

Sustainable innovation has become indispensable for enterprises, governments, and non-profit organizations (Nguyen et al., 2019; Khaled et al., 2021; Van der Waal & Thijssens, 2020). Survival and success in the new competitive markets require flexible and dynamic capabilities. Unexpected times, like market gyrations, political unpredictability, climate change, wars, and health challenges, must be further tested for long-term viability. Organizations must identify and draw on their innovative ability to cope with difficult times. The research of Lee and Trimi (2021) presents convergence innovation driven by the exponential integration of various objects, technologies, concepts, and strategies, as well as a new organizational capacity based on exponential fusion as a general principle.

We can trace extensive work on technology convergence and innovation link in the research Hacklin et al. (2004, 2005); Hacklin (2008); Hacklin et al. (2009, 2010, 2013b, a); Hacklin and Wallin (2013), Steinmueller (2000). Many believe that knowledge resources and the convergence of technology will have far-reaching effects on organizational knowledge, including depersonalization and interdisciplinarity. The phenomenon of technological convergence has gained prominence over the last decade. The fusion of different knowledge from the past provides the basis for the formation of new applications and business models. Such breakthroughs are emerging in industries, destroying previously recognized divisions between industries. Convergence could lead to significant changes in existing industries Blanco et al. (2020), Hussain et al. (2019), Spulbăr et al. (2020).

Previous research examines the impact of the convergence of science and technology on R & D operations to identify them, Lee et al. (2018). We see that the scientific capacity of organizations and the spread of regional knowledge correlate positively with the impact of innovation.

The study highlights how different knowledge sources influence innovation and underscores the importance of converging impacts at the knowledge level of it. Technological convergence leads to convergence at the industrial level, knowledge, discipline, and firm level. As technology fusion through melting various core technologies creates new product markets, it develops an innovation transition path in the business. This is also happening in the service and industry 4.0 Frank et al. (2019). A non-profit research and development organization develops its innovation mechanism to enable end-to-end open innovation. Case studies showed the platform-based open innovation framework is successful in open innovation, and in industrial research and technology, the organization results in commercialization, Wang et al. (2021).

Converging and globalizing markets (increasingly overlapping) also drive convergence innovation through combinatorial market innovation Geiger and Kjellberg (2021). When we discuss market innovation, we speak of institutions creating an opportunity for new approaches to doing business, Ekman et al. (2021). Digital innovation plays a substantial role in convergence innovation Vaio et al. (2021), Kregar et al. (2019).

No previous reports in the literature provide strong empirical evidence to support the convergence innovation hypothesis. Previous research showed that convergence innovation is a consequence of technological, knowledge, and market convergence in a globalized world. This is generally accepted in literature, from which we can conclude that convergence innovation exists. The literature was reviewed for possible methods to support this hypothesis. The nonlinear time-varying factor convergence test is the most influential approach from the literature we use in this study to provide empirical evidence supporting the convergence innovation hypothesis.

Research objective and methodology

To study convergence and convergence clubs in convergence innovation, this study uses annual data from 1995 to 2017 for twenty-nine countries. The central database we use in the study is Stehrer et al. (2019). In 2019, the EU KLEMS released two crucial data sets: the statistical and analytical databases. While this type of national accounting methodology follows official national accounting data provided by national statistical institutes, the other accounts give intangibles, including investment flows and assets, highlighted in recent literature, a more prominent role (Chen et al., 2021). More differentiated information is provided in the statistical databases. Growth is divided into tangible information and communication capital and other non-ICT assets. Not only that but also additional asset types never declared capital are reported in the analytical database. These asset types include recently proposed properties and competencies Adarov et al. (2019), Corrado et al. (2005), Corrado et al. (2009), Corrado et al. (2018), Steinmueller (2000), O'Mahony et al. (2017), Haskel and Westlake (2018). Although significant problems are addressed, these gaps in the framework give important insights into the extent and trends that need to be extracted from these data. The motive and theoretical background behind using data on intangible assets as a proxy for convergence innovation lies in the fact that we want to assess convergence innovation across countries. According to Haskel and Westlake (2018), data supporting this point are not only limited but also indirect. To measure convergence innovation for 26 countries, including ex-transitional economies, using data Stehrer et al. (2019), Adarov et al. (2019) from 1995 to 2017. Data sample selection was based mainly on data availability and best fit for the modelling purpose. Firms' innovative property is assessed by Design - an intangible asset defined as gross fixed capital formation in design and other product development (current prices, national currency in millions). Firms' innovativeness can be best assessed by comparing investments in design and new product developments at the industry level. Using design and new product developments (investments in firms' intangible assets), it is possible to assess the level of inventiveness at the industry level (industry-level data).

Following Phillips and Sul (2007b, a, 2009); Du (2017); Sichera and Pizzuto (2019), the model for convergence testing on convergence innovation takes the form

$$\log C_{it}^{0} = \delta_{it}^{0} \log C_{t}^{0} + e_{it} \qquad (1)$$

with $log\ C_{it}^{0}$ as a convergence innovation indicator for the i_{th} country, $log\ C_{t}^{0}$ being a common trend across countries with idiosyncratic business cycle components e_{it}. Testing for the null hypothesis of no convergence innovation (convergence innovation is not present) follows.

For details on convergence innovation testing and proofs, see Phillips and Sul (2007a, 2009, 2007b).

Table 1: List of Countries in the Sample.

1. AT-Austria	17. JP-Japan
2. BE-Belgium	18. LT-Lithuania
3. BG-Bulgaria	19. LU-Luxembourg
4. CY-Cyprus	20. LV-Latvia
5. CZ-Czech Republic	21. MT-Malta
6. DE-Germany	22. NL-Netherlands
7. DK-Denmark	23. PL-Poland
8. EE-Estonia	24. PT- Portugal
9. EL-Greece	25. RO-Romania
10. ES- Spain	26. SE-Sweden
11. FI-Finland	27. SI-Slovenia
12. FR-France	28. SK-Slovak Republic
13. HR-Croatia	29. UK-United Kingdom
14. HU-Hungary	
15. IE-Ireland	
16. IT-Italy	

Source: Stehrer et al. (2019).

The countries included in the sample for convergence of innovation are listed in Table 1.

Countries were selected based on the availability of the data and the methodology defined in Stehrer et al. (2019). We use this statistical database because it contains balanced data on innovation and a balanced panel sample required for convergence tests to determine the innovation of convergence clubs.

We use the procedures and tests described in Phillips and Sul (2007b, a, 2009) to form innovation clusters. The t-test for the null hypothesis of convergence in innovation takes the following form

$$H_0: \delta_i = \delta \text{ and } \alpha \geq 0 \tag{2}$$

following *log t* regression equation

$$\log \frac{H_1}{H_t} = -2 \log(\log t) = \alpha + \beta \log t + u_t, \text{ for } t = [rT], [rT] + 1, \ldots, T \tag{3}$$

with a relative transition component Sichera and Pizzuto (2019)

$$h_{it} = \frac{X_{it}}{N^{-1} \sum_{i=1}^{N} X_{it}} = \frac{b_{it}}{N^{-1} \sum_{i=1}^{N} b_{it}} \tag{4}$$

We continue with the above model and classify countries according to their initial innovation indicators (Inn). To form final convergence clubs, we perform a *t*-test on all pairs of initial

$$H_t = N^{-1} \sum_{i=1}^{N} (h_{it} - 1)^2 \to 0 \text{ as } t \to \infty \tag{5}$$

convergence clubs, invalidating the t-test for all pairs of initial convergence clubs. Finally, we use relative transition parameters to determine cross-sectional means between convergence clubs (plotting relative transition curves between clubs). Plots of relative transition parameters between clubs show a trend of convergence or divergence in and between clubs. The data entered in the *t*-test are pre-filtered using the form (Hodrick & Prescott, 1997)

$$\min_{\{g_t\}_{t=-1}^{T}} \left\{ \sum_{t=1}^{T} (y_t - g_t)^2 \right. \tag{6}$$

$$\left. + \lambda \sum_{t=1}^{T} [(g_t - g_{t-1}) - (g_{t-1} - g_{t-2})]^2 \right\}$$

As discussed in, any possible bias in the smoothing parameter (annual data) is adjusted Hamilton (2017). Table 2 presents the statistical properties of the data series in the sample.

Table 2: Statistical properties of the data sample

Variable	Obs	Mean	Std.Dev.	Min	Max
id	667	15	8.37	1	29
year	667	2006	6.63	1995	2017
Inn	664	7.75	2.58	2.34	14.9

Source: Authors' own research

The following section summarizes the findings of a convergence test conducted on innovation indicator (Inn) to identify innovation convergence clubs.

Results

Global innovation trends show a distinct convergence pattern. We observe top innovative countries like Japan, Hungary, Czech Republic, Sweden, Italy, and Denmark (Figure 1).

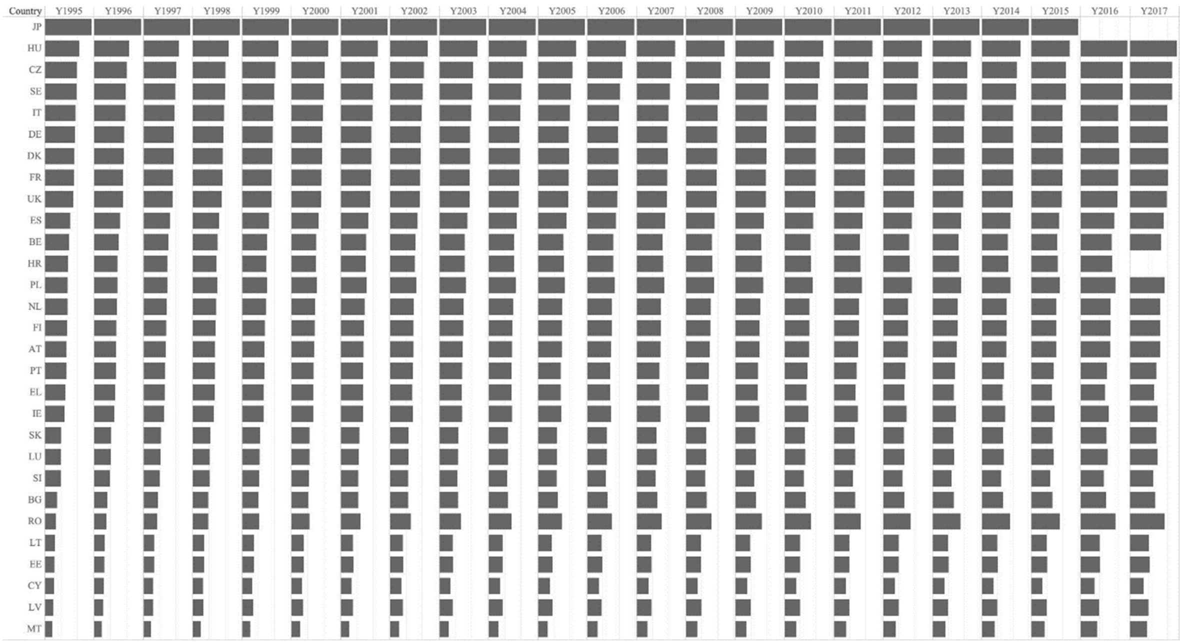

Fig. 1. Innovation Trend in Selected Economies 1995-2017.
Source: Authors' own research

Figure 1 shows a convergence pattern in gross fixed capital formation in design and other product development (Inn) at industry-level data.

The log (t) regression coefficient, standard errors, and t-statistics are listed in Table 3. Since the t statistics for (Inn) are less than the test statistics $t_{\hat{\beta}} < -1.65$, the null hypothesis of sample convergence in innovation is rejected at the 5% level for the entire sample. We find no evidence to support the hypothesis of innovation convergence across the entire sample (29 countries). There are significant differences in the innovation dynamics of the countries and groups of countries included in the sample.

We identify convergence clubs after rejecting the innovation convergence hypothesis for the sample. Following establishing initial convergence clubs (29 countries), we examine the possibility of club mergers to obtain the final convergence club structure.

Using (Inn) as an innovation indicator, we identify convergence clubs from 29 countries using convergence test models.

The following table summarizes the final convergence clubs and countries identified based on the *log* (*t*) test results for the (Inn) indicator (log *t*-test results and club merging test results).

Table 3: Gross fixed capital formation in design and other product development at the industry level data, change in the natural log Convergence Club Classification (Inn)

Initial		*Test of club merging*				*Final*	
Club1 [5]	*0.401* *(1.488)*					*Club 1[18]*	*-0.100* *(-0.810)*
Club2 [7]	*0.096* *(1.923)*	*Club 1+2*				*Club2 [8]*	*0.196* *(17.3)*
Club3 [6]	*0.042* *(0.759)*		*Club 2+3*			*Group [3]*	*-0.801* *(-171.7)*
Club4 [8]	*0.196* *(17.3)*			*Club 3+4**			
Group5 [3]	*-0.801* *(-171.7)*				*Club 4+5**		

Source: Authors' own research

From Table 3, we observe a strong convergence pattern in innovation from 1995 to 2017. Initial innovation convergence clubs identified by the *log* (*t*) test list four convergence clubs and one non-convergent group. After testing for Club merging properties, the final convergence list includes two distinct convergence clubs and one non-convergent group (rejecting the innovation convergence hypothesis among the countries in the group and sample).

Final convergence clubs' lists:

Convergence club 1: AT-Austria, BE-Belgium, BG-Bulgaria, DE-Germany, DK- Denmark, ES-Spain, FI-Finland, FR-France, HR-Croatia, HU-Hungary, IT-Italy, JP-Japan, LU-Luxembourg, MT-Malta, PL-Poland, RO-Romania, SE-Sweden, SK-Slovak Republic, UK-United Kingdom.

Convergence club 2: BG-Bulgaria, EE-Estonia, EL-Greece, IE-Ireland, LT-Lithuania, LV-Latvia, PT-Portugal, SI-Slovenia.

Non-convergent group 3: CY-Cyprus, CZ-Czech Republic, NL-Netherlands. Figure 2 shows the average innovation transition paths for all initially identified clubs.

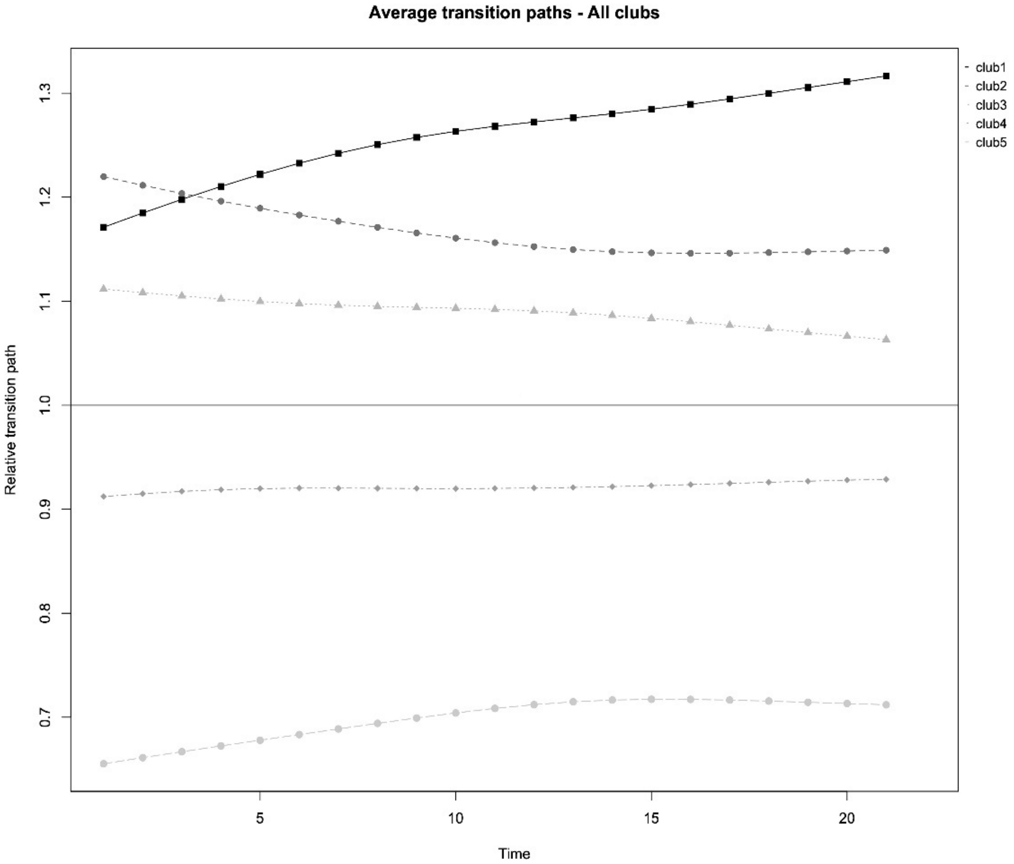

Fig. 2. Clubs' innovation convergence relative transition path.
Source: Authors' own research

Figure 2 displays the initial clubs' innovation convergence relative transition path with five clubs. After testing for club merging, we find two convergence clubs and one non-convergent group. We can observe a strong convergence in innovation for the analyzed sample at the industry and country levels. The deterministic nature of innovation convergence is explored across clubs and countries in the sample.

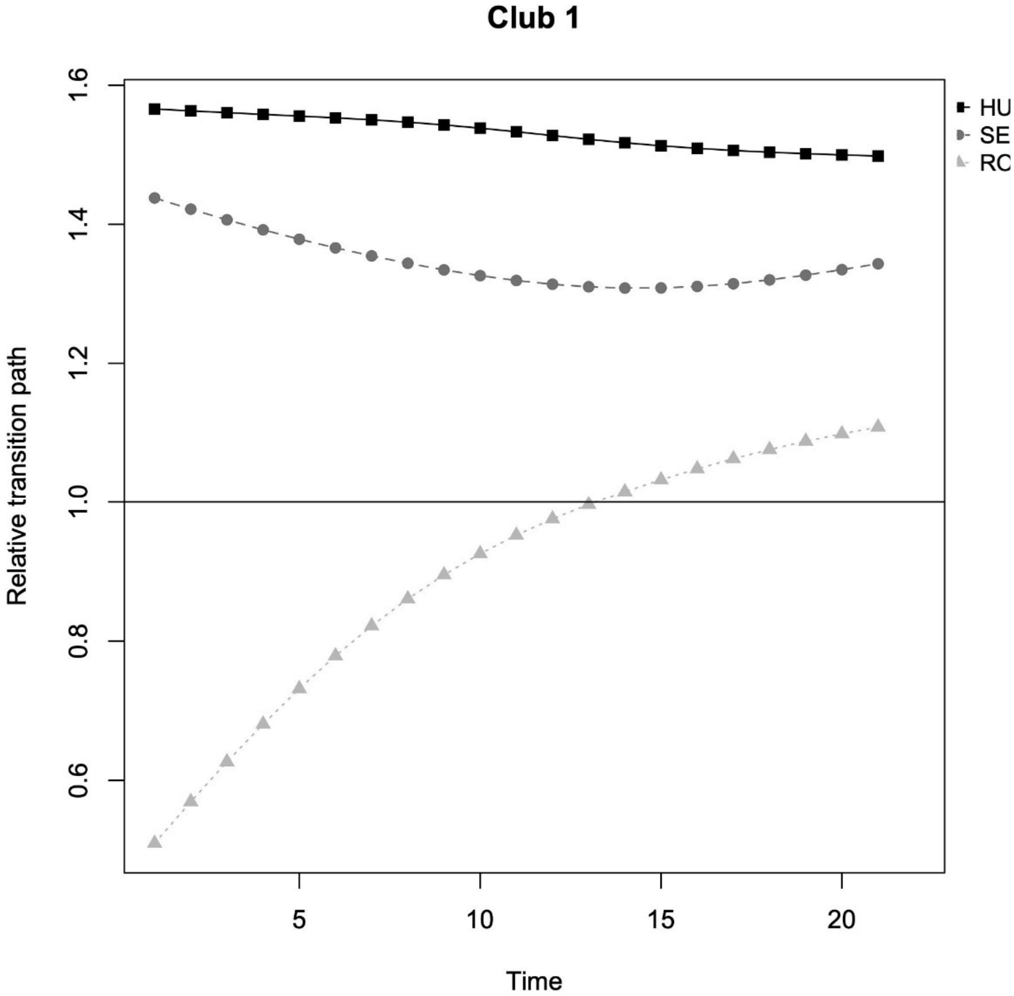

Fig. 3. Innovation Convergence in Club 1.
Source: Authors' own research

Figure 3 shows that innovation convergence in Hungary (HU) and Sweden (SE) follow close relative transition paths. Romania (RO) displays strong catch-up dynamics for innovation convergence, proposing as a candidate for studying innovation convergence determinants over the observer period. Future studies on innovation convergence could research the factors behind Romania's strong innovation catch-up dynamics from 1995-2017.

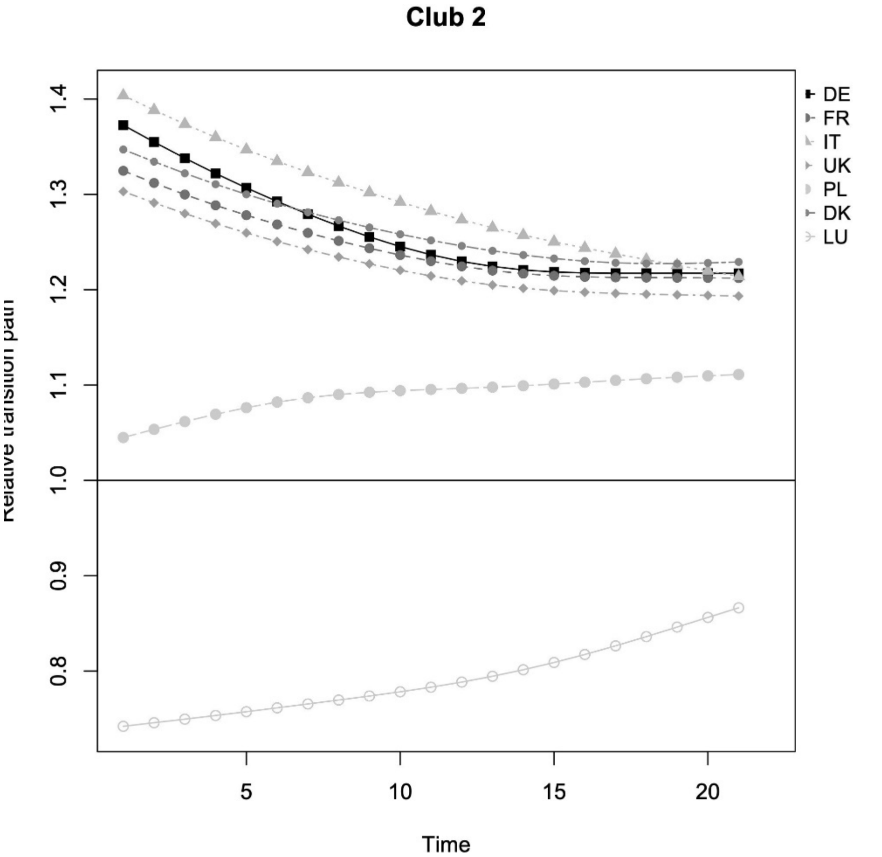

Fig. 4. Innovation Convergence in Club 2.
Source: Authors' own research

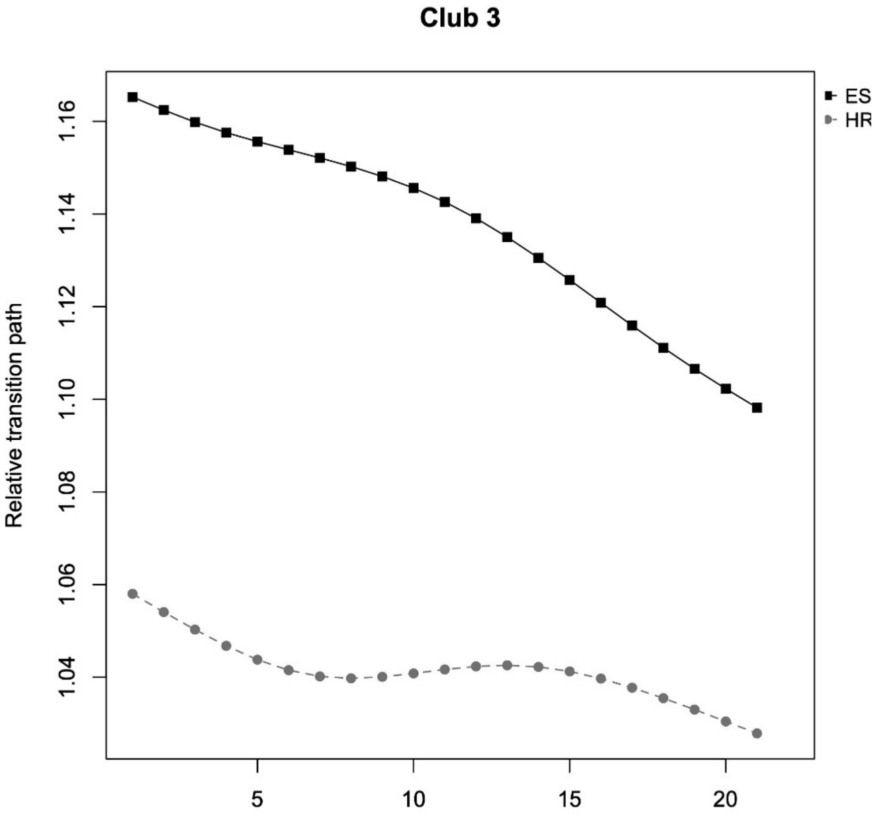

Fig. 5. Innovation Convergence in Club 3.
Source: Authors' own research

Figure 4 also supports strong innovation convergence dynamics for countries in Club 2. We can notice a decline in the relative transition path for most countries (slowing down in innovation) in Club 2. Poland and Luxembourg are exceptions with progressing innovation in both countries. Luxembourg shows a strong catching-up innovation dynamics that should be studied more deeply.

Figure 5 shows declining relative transition paths in innovation for Spain and Croatia from 1995-2017. We can observe a steep drop in innovation for Spain and a relative drop in innovation for Croatia. Both countries share a negative relative innovation transition path.

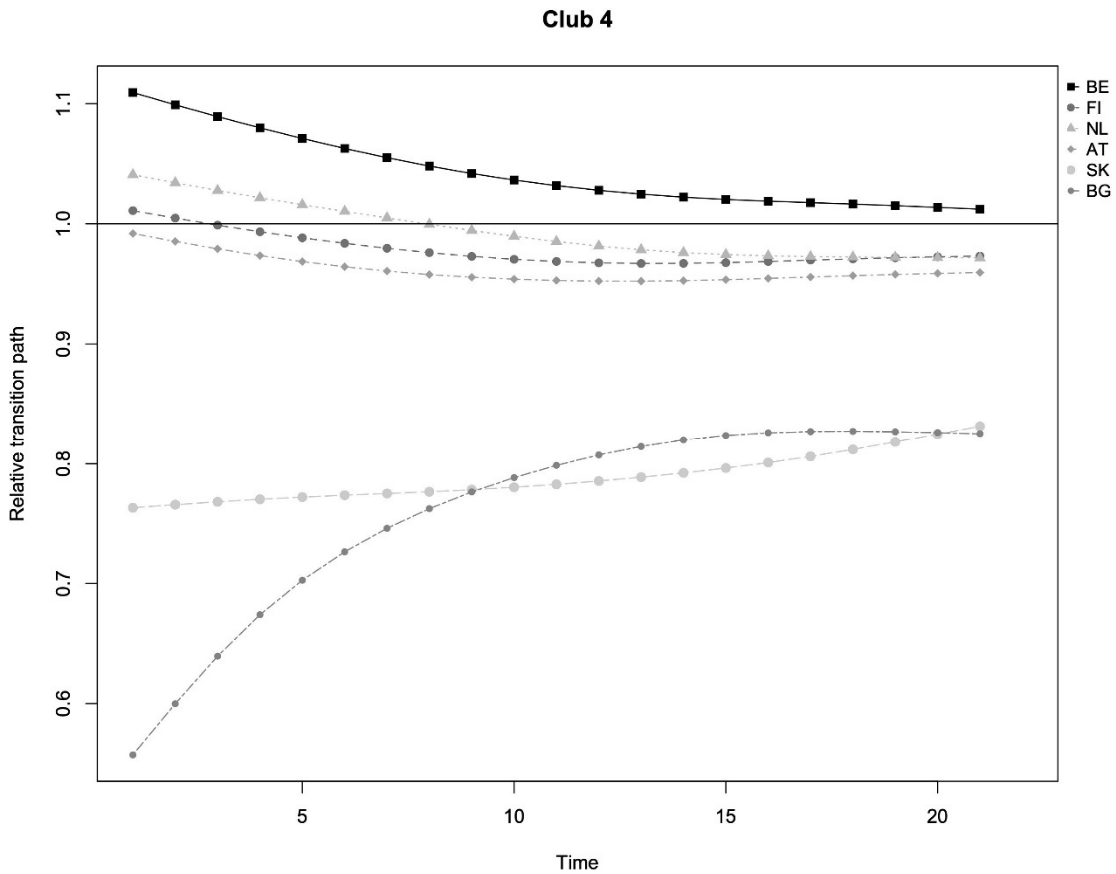

Fig. 6. Innovation Convergence in Club 4.
Source: Authors' own research

Innovation dynamics in the Club 4 are strongly converging for most countries, with Slovakia and Bulgaria showing different relative transition paths for innovation. Both countries display convergence in innovation with the rest of the group (Figure 6).

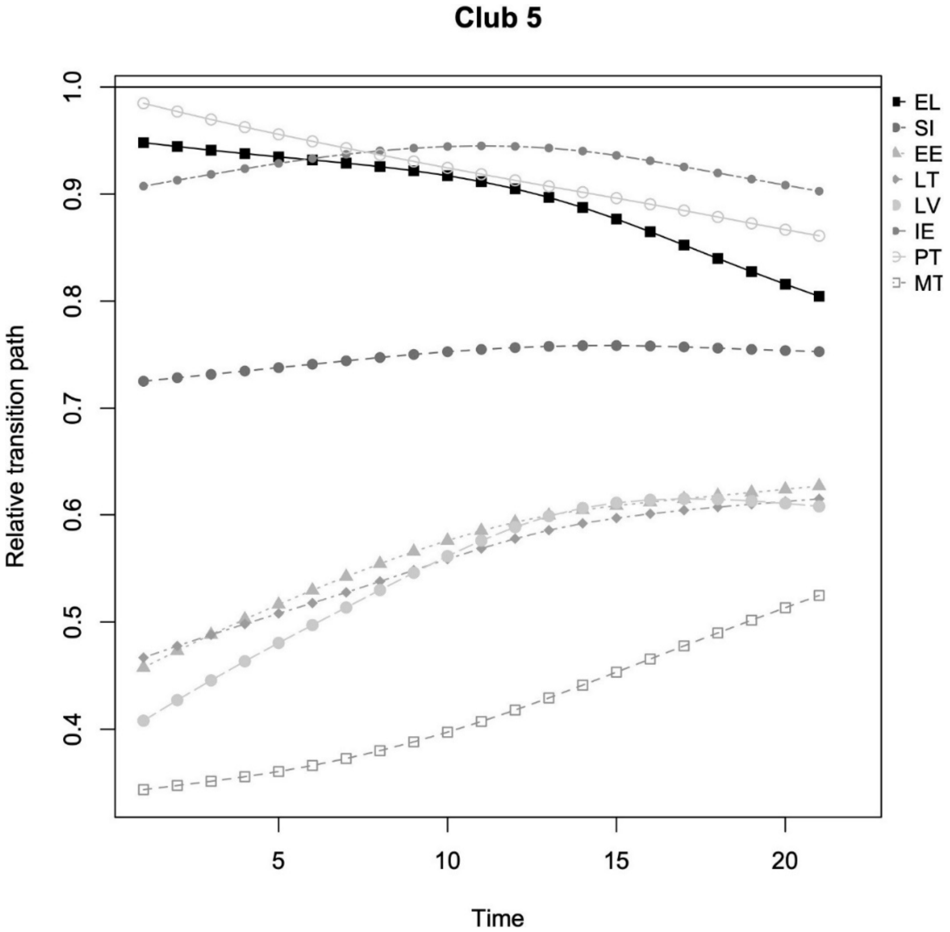

Fig. 7. Innovation Convergence in Club 5.
Source: Authors' own research

Figure 7 displays a clear convergence in the relative transition path for innovation, including all countries in Club 5. Slovenia displays a high persistence in innovation convergence, an average of 0.7 over the observed period. Other countries in the Club show convergence in innovation, with Malta, Latvia, Estonia, and Lithuania converging with the rest of the group.

In the next section, we compare our results with previous studies on innovation convergence.

Discussion

Literature lists endogenous drivers (firm-level) and exogenous drivers (industry-level) innovation convergence determinants Hacklin (2008). Innovation convergence results from companies' search for innovative opportunities in other economic sectors, the creation of new technologies that connect individual products to a more integrated global system, discovering new technologies that meet the needs already met by existing technologies, diversifying, ensuring technical scope growth as well as development in the sectors like heavy industry, mining, and material processing sector, with start-ups contributing to new managerial leadership. Our empirical results support this thesis by isolating firms' convergence for the selected sample. We test the innovation convergence hypothesis to check if innovation convergence on the firms' level follows stochastic or deterministic behaviour. In the case of the stochastic nature of innovation convergence, clubs should be clustered around a few countries, resulting in many convergence clubs. Here we show this is not the case, providing empirical validation on the deterministic nature of innovation convergence on the firms' level from 1995-2017. In summary, firms' interest in searching for innovation possibilities in pursuing profits on the market drives innovation convergence Kodama and Kimura (2020); Simeth and Raffo (2013); Yun and Kim (2016); Hussain et al. (2019); Geiger and Kjellberg (2021).

Innovation convergence on the firms' level is usually listed as endogenous deterministic behaviour. What about exogenous stochastic/deterministic behaviour of innovation convergence? Innovation convergence on the industry level is driven by main determinants, as listed in Hacklin (2008):

- Changes in technology, sectors – from obtaining resources within mining industry to their processing within further sectors,

- Overflow of information,
- The emergence of collective knowledge pools,
- Through using common standards, we can enhance connectivity and interconnectedness.
- Many devices, which are becoming increasingly multifunctional,
- The pervasiveness of information,
- Deregulation (Teece, 2010),
- The increasing similarity of consumer demands across segments of the population,
- Catalyst fundamental for information production and mutual transmission, opportunities for product bundling are expanding (Snihur and Tarzijan, 2018).
- The pervasiveness of provided product components,
- Changes in the law,
- Customer segment homogenization due to changing demographics
- Bundling of products
- The desire of customers for "one-stop" shopping,
- Globalization (Di Vaio et al., 2021),
- Digitalization,
- Consumer demands are becoming increasingly complex (Zott and Amit, 2007),
- Technological dispersion,
- Existing value chains are altered through market forces.
- Changes in society (Nylén, 2021; Häbel & Hakala, 2021).

We can observe the same deterministic behaviour in innovation convergence on the industry level that we already saw on the firms' level. Exogenous factors of change in innovation convergence listed above share the same convergence (clustering) pattern with the final two convergence clubs and one non-convergent group. Innovation convergence follows the same relative transition path (main determinants change pattern) for countries in the innovation convergence club 1. Countries in the innovation convergence clubs 1 share the same pattern (change) over time in the main determinants listed above. Countries in innovation convergence club 2, share a different pattern of change in innovation convergence determinants from the countries in innovation convergence club 1. Future studies on innovation convergence could research the factors behind Romania's strong innovation catch-up dynamics from 1995-2017. Innovation convergence relative transition path depends both on firm-level Kodama and Kimura (2020); Simeth and Raffo (2013); Yun and Kim (2016); Hussain et al. (2019); Geiger and Kjellberg (2021) and industry-level factors Lee et al. (2018); Song et al. (2017); Boussemart et al. (2020); Jeong and Lee (2015); Kim and Lee (2020); Lim et al. (2018); Zhou et al. (2019); Kim et al. (2014); Lee et al. (2015); Hacklin et al. (2005).

The majority of the countries in the sample show a clear convergence pattern in innovation relative transition paths. Exceptions are Cyprus, Czech Republic, and the Netherlands following a divergent innovation path - a divergent group we isolate in the convergence analysis. Innovation determinants in these countries drive innovation relative transition path away from the rest of the countries in the sample. To understand why innovation in these countries is diverging from the rest, it should be studied in more detail to learn which factors are most important behind innovation dynamics.

Conclusion

Innovation convergence shows deterministic behaviour on the industry level, as our study shows for 29 economies during 1995-2017. Our study is the first to explore the endogenous and exogenous innovation convergence theory, using Phillips and Sul (2007a, b, 2009) growth convergence theory as background. We define "innovation convergence as a deterministic process resulting from a deterministic change in micro and macro innovation determinants." Using an innovation convergence nature, we should strive to identify the main innovation determinants in future studies. Here we show that innovation convergence is an empirical fact, and the same innovation convergence phenomena will allow us to uncover factors behind innovation processes - globally, nationally, industry-level, and using big data on the firms' level.

For the sample of 29 countries from 1995 to 2017 using industry-level data, we identify two significant convergence clubs and one divergent group (Cyprus, Czech Republic, Netherlands). Such empirical fact implies that the main factors behind innovation dynamics in the observed countries are closely moving on a joint relative transition path. More advanced economies in the sample are behind the starting level of 1995, indicating that innovation processes are slowing down. Ex-transitional and former socialist economies are firmly catching up, driving innovation in the EU. Empirical evidence indicates that innovation singularity could appear as a significant barrier and limiting factor for firms' and countries' growth in the future. The practical implications of our study are two-fold: on a micro and macro level. On a micro level, owners and managers should be aware of innovation singularity and take steps to build a buffer zone against it. The solutions can be found in continuous product diversification, human capital improvement, capital deepening, digitalization, and artificial intelligence integration.

On the macro level, policymakers must look at slowing innovation as a robust and limiting factor for future economic growth. Also, the EU should be aware that innovation in advanced economies is falling and that innovation dynamics drive the innovation process in new member states (mainly ex-socialist economies). In the close future (2030), innovation processes in new member states will reach the convergence level of more advanced economies in the EU, leading to a possible innovation stall at the EU level (Fedajev et al., 2021).

Our study is limited by the availability of the data, resulting in a sample constraint - time series and panel data limitation. To study the innovation convergence deeper and correct for possible bias, a more extensive set of available indicators is desirable. However, both more extensive time series, panel, and additional indicators' availability is not a limiting factor in the scientific contribution and empirical knowledge here, but rather a way for future improvement of the innovation analysis. Future studies using additional indicators could use logistic regression models to unravel innovation and the main factors further behind.

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