Join the club! Dynamics of global ESG indices convergence*

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Abstract

We investigate the convergence behaviour of 18 ESG stock market indices from a global perspective. We rely on the convergence tests and clustering procedures by Phillips and Sul (2007, 2009) which are based on a time-varying nonlinear panel factor model. In particular, we find a structural break in May 2019. Prior to the break, we identify Brazil and China as co-diverging units and find some heterogeneity in relative convergence clusters for the remaining countries. After the break, we do not find only relative, but also level convergence amongst all considered countries in one single club. The structural break and its timing can be linked to significantly increased global investor attention for ESG.

Keywords: ESG, equity market convergence, panel convergence, variance trend break

JEL classification: C23, C32, C33, C58, E13, Q56

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1 Introduction

ESG regulations converge around the world and the question is whether global ESG stock market indices do so as well. Major players like financial institutions, organisations and countries have joined the club to promote the introduction and enhancement of ESG concepts. There are numerous incentives by international organisations like the United Nations, European Union and OECD to protect the climate, to enhance social standards, e.g., in supply chains or health and safety provisions, and improve corporate structures. These changes do not stop at the finance profession and investment industry either. Instead, major financial decision tool providers like MSCI steadily increase the number of ESG indices and consequently, the amount of globally available ESG equity ETFs rapidly increases. At the same time, the assets under management of ESG ETFs grow rapidly, i.e. through the emergence of new trading platforms and online brokers which offer retail investors a simple way to invest in ESG ETFs. So, naturally the question emerges, if there is some convergence of country-specific ESG indices. Finding an answer is vital because it has major consequences for portfolio construction and global risk diversification.

To investigate the convergence behaviour of ESG stock market indices, we apply the panel data convergence model of Phillips and Sul (2007, 2009). Their approach extends the more classic cointegration framework for analysing convergence. Earlier studies on stock market and interest rate convergence are inter alia Caporale et al. (1996), Baum and Barkoulas (2006), Mylonidis and Kollias (2010), Sibbertsen et al. (2014), and Frömmel and Kruse (2015). The aforementioned studies use (fractional) (co)-integration tests (under structural breaks) to investigate convergence in financial markets. Phillips and Sul (2007, 2009) established the concept of relative convergence to address inherent difficulties with the concept of level convergence. It leads to a logarithmic trend regression model which is estimable by OLS and allows for standard asymptotic inference. The more general procedure by Phillips and Sul (2009) gained huge popularity in convergence studies and is applied by Panopoulou and Pantelidis (2009), Burnett (2016), and Ulucak and Apergis (2018) for CO_2-related and environmental research, by Rughoo and Sarantis (2014) for banking and GDP growth by Monfort et al. (2013) as well as price, labour, income and productivity convergence by Fritsche and Kuzin (2011). Most closely related is Apergis et al. (2014) who analyse the convergence behaviour of equity markets of 42 different countries and Apergis et al. (2020) who study the convergence of eight major cryptocurrencies.[1]

[1]For a detailed literature review of convergence studies, we refer to Apergis et al. (2014).

The structure is as follows: Section 2 describes the used data set and in section 3, the applied panel (club) convergence testing approach is explained. In section 4, we show the analysis and results while section 5 concludes.

2 Data

We consider $N = 18$ international total return stock market indices from August 2013 to December 2021 ($T = 101$) obtained from REFINITIV, see Table 1. To account for the complete value generation which an investor receives by investing in indices via ETFs, we use real monthly total return price data expressed in USD. Using an earlier starting point would have significantly reduced the number of cross-sectional units N as many ESG indices do not have a long track record. For comparability, we use the MSCI ESG Leaders index group which is based on (nearly) the same methodology for all investigated countries.[2]

Australia	Brazil	Canada
China	Hong Kong	India
Indonesia	Japan	Korea
Malaysia	Russia	South Africa
Sweden	Switzerland	Taiwan
Thailand	UK	USA

Table 1: MSCI ESG Leaders indices

3 Methodology

We apply the popular methodology of Phillips and Sul (2007, 2009). It does not rely on any stationarity assumption, it is able to deal with different transition paths to convergence and it finally provides a meaningful clustering algorithm. The approach is not only able to test the hypothesis of convergence in the complete panel data set[3], but instead it is also able to identify different convergence clubs and divergent units.

[2]Naturally, the question of a control group emerges. In many studies concerning the investigation of ESG indices, ESG indices are simply compared to the mother index which includes not only ESG-compliant companies but also "neutral" and non-ESG firms. Using such an approach results in a serious identification issue since companies are listed in both indices. As MSCI (and others) do not calculate "non-ESG indices" per se, we neglect such comparisons.

[3]It is recommended to use a balanced panel data set - like in our case. Nevertheless, it is also possible to apply the procedure to unbalanced panels. In fact, the log-test regression requires the computation of H_t which allows for missing values in X_{it}. However, such missing values might introduce a bias and decrease efficiency.

The panel units X_{it} are stated as the decomposition of the factor loadings b_{it} and the common trend function μ_t (which includes both common deterministic and stochastic trends):

$$X_{it} = b_{it}\mu_t. \tag{1}$$

The relative transition parameter h_{it} is defined as:

$$h_{it} = \frac{X_{it}}{\frac{1}{N}\sum_{i=1}^{N} X_{it}} = \frac{b_{it}}{\frac{1}{N}\sum_{i=1}^{N} b_{it}}. \tag{2}$$

Under convergence, there has to be a common limit in the transitions of each panel unit and thus, $h_{it} \to 1 \; \forall i = 1, \ldots, N,$ as $t \to \infty$. For the cross-sectional variance H_t it holds:

$$H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{it} - 1)^2 \to 0 \text{ as } t \to \infty. \tag{3}$$

Phillips and Sul (2007, 2009) state the time-varying factor loadings in a semi-parametric way:

$$b_{it} = b_i + \frac{\sigma_i \xi_{it}}{L(t)t^{\alpha}}. \tag{4}$$

Here, b_i is an individual-specific component, σ_i is a scaling factor and ξ_{it} is an error term which is $i.i.d.$ $(0,1)$ across i, but weakly dependent over t, $L(t)$ is a slowly varying function and α is the convergence rate. The null hypothesis of convergence H_C and the alternative of divergence H_D are given as:

$$H_C : b_i = b \text{ and } \alpha \geq 0 \; ,$$

$$H_D : b_i \neq b \; \forall i \text{ or } \alpha < 0 \; .$$

Testing H_C involves following OLS $\log t$ regression:

$$z_t = a + \gamma \log(t) + u_t. \tag{5}$$

Here, $z_t \equiv \log\left(\frac{H_1}{H_t}\right) - 2\log[L(t)]$, where the second term represents a penalty term to increase the power. The time index $t = [rT], [rT]+1, \ldots, T$, where $r \in (0,1)$ is chosen to enhance size properties of the test.[4] Last, $L(t) = \log(t+1)$ and u_t is an error term. We have $\gamma = 2\alpha$. If $\gamma \geq 2$ ($\alpha \geq 1$), there

[4] As suggested in Phillips and Sul (2007), we set $r = 0.2$ for the given sample size.

is level convergence. But in contrast, if $0 \leq \gamma < 2$ ($0 \leq \alpha < 1$), there is only relative convergence. For $\gamma < 0$ ($\alpha < 0$), there is divergence.

H_C is tested based on a one-sided t-statistic (t_γ) with HAC standard errors with a standard normal limiting distribution.[5] The convergence hypothesis is rejected at the 5% level if $t_\gamma < -1.65$. In this case, the clustering algorithm of Phillips and Sul (2007, 2009) is applied to find different clubs of convergence and divergent units as follows:

1. **Cross-section last observation ordering**: The panel units X_{it} are ordered based on the last observation of the period.

2. **Core group information**: The $\log t$ regression is applied to the first k highest units ($2 \leq k < N$) and then, k is maximized based on the following optimization system: $k^* = \arg\max_k t_\gamma(k)$, s.t. $\min t_\gamma(k) > -1.65$. If k^* is equal to the number of panel units N, the complete panel converges. In contrast, if $\min t_\gamma(k) \leq -1.65$ for $k = 2$ the first unit is removed and the procedure starts, again. If the condition is not fulfilled for any following pair of units, the complete panel diverges.

3. **Sieve the data for club membership**: After k^* is identified, one implements the $\log t$ test for k^* adding each remaining unit one at a time. If $t_\gamma(k) > c^*$ (with c^* set to 0), a new unit is put in the convergence club. All these units build the first convergence club.

4. **Recursion and stopping rule**: If panel units are not added to the convergence club identified in step 3, these units are grouped and the $\log t$ test is applied to them. If $t_\gamma(k) > -1.65$, there is one additional convergence group in the panel but if $t_\gamma(k) \leq -1.65$, the steps 1 to 3 have to be repeated for these units. If then no further convergence clubs are found, the left units diverge.

In the last step, a merging algorithm of Phillips and Sul (2007, 2009) is applied to handle potential overidentification of clusters. The $\log t$ test is run based on the first two groups which are merged if $t_\gamma(k) > -1.65$. Next, groups are added to the formerly merged group as long as $t_\gamma(k) > -1.65$. If the convergence hypothesis is rejected, all previous groups (but not the last one) converge. The merging algorithm is restarted, beginning from the group for which the convergence hypothesis did not hold.

[5] Phillips and Sul (2007) show by means of Monte Carlo simulations that their procedure performs well in terms of size and power, especially if T is larger than 50 (see pages 1802-1803 and their Figure 3). In our empirical analysis, we rely on asymptotic inference as their simulations indicate that the procedure performs well for sufficiently large T. To the best of our knowledge, validity of any bootstrap method has not been proven yet in this particular framework.

4 Results

Applying the previously mentioned methodology to our Hodrick-Prescott-filtered log real prices, we find that the convergence hypothesis for the complete panel (with $N = 18$) is rejected at the 5% level. Applying the clustering algorithm results in the identification of two different convergence clubs. For both clubs, the null hypothesis of convergence cannot be rejected at the 5% level (see Table 2).

Convergence test without clustering					
	n	γ	$se(\gamma)$	t-stat	p-value
Club 1	18	-0.833	0.053	-15.595	0.000
Convergence test with clustering					
	n	γ	$se(\gamma)$	t-stat	p-value
Club 1	16	-0.014	0.106	-0.128	0.449
Club 2	2	1.087	1.167	0.932	0.824

Table 2: Results of convergence analyses

The second club consists of Brazil and China, while in the first club are all remaining countries. To test for robustness, we re-run the clustering algorithm excluding either Brazil or China or both of them. The previously identified Club 1 remains in all three cases. The relative transition paths for Brazil and China further suggest that they are actually co-divergent rather than convergent (see Figure 1). The relative transition curves clearly indicate a joint divergence behaviour. Importantly, we observe a reversed behaviour in the last third of the sample where the relative transition curves tend towards unity.[6] This particular behaviour is further investigated below. In Table 2, we report the estimate for γ which is 1.087 and thereby suggesting relative co-divergence.

[6]There has been a change in importance of ESG-related topics in China. This can e.g. be seen in Weber (2013), Broadstock et al. (2021), Feng et al. (2022), and Li et al. (2022) and in the efforts of the China Securities Regulatory Commission (CSRC).

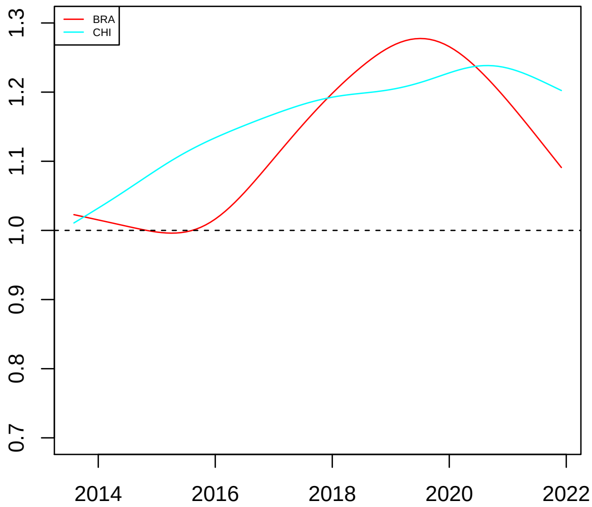

Figure 1: Relative transition paths h_{it} of Club 2 members

In Figure 2, the relative transition paths h_{it} for all 16 members of Club 1 are provided.

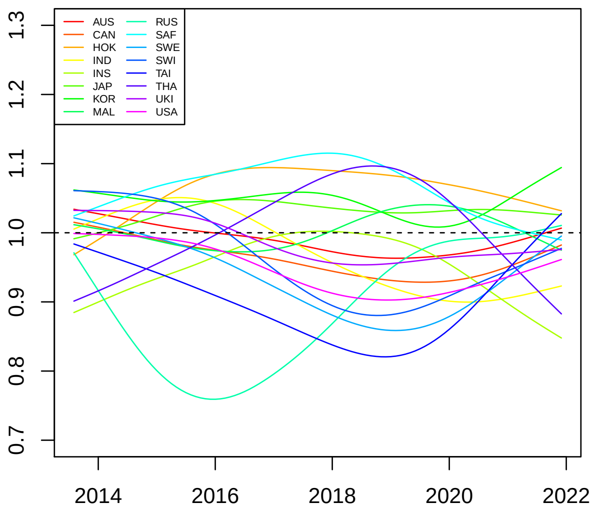

Figure 2: Relative transition paths h_{it} of Club 1 members

Rather than stopping at this point, we visually inspect the cross-sectional panel variance H_t and the related series z_t. The plot clearly illustrates that while H_t increases from 2013 onwards, there is a turning point in mid 2019 and from there on, the cross-sectional variance decreases (see Figure 3). While an accumulation of cross-sectional variance is indicative of common divergence, its diminishing behaviour suggests common convergence.

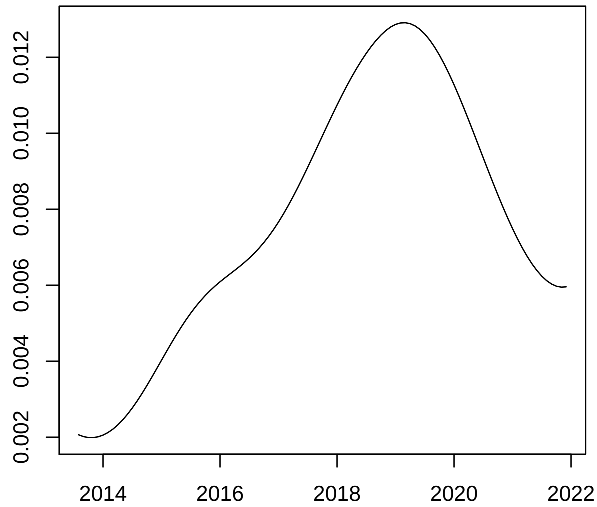

Figure 3: Development of cross-sectional variance H_t over time

A similar, but inverse, picture is painted for z_t. The clear turning point in 2019 suggests that global common divergence has changed towards global common convergence (see Figure 4).

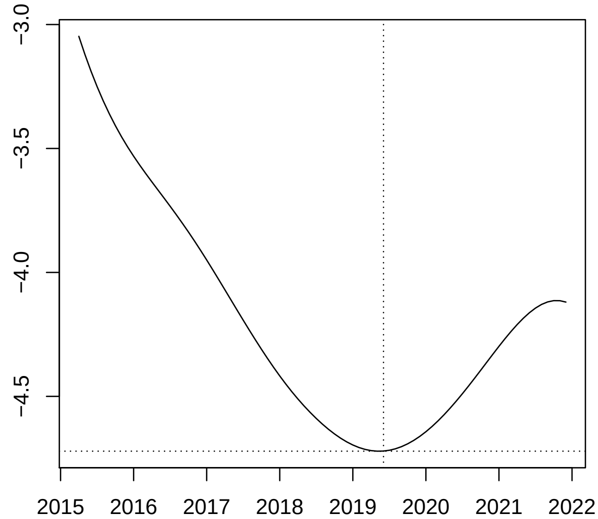

Figure 4: Development of z_t over time

To statistically validate our visual finding of a turning point in z_t, we model it using a structural break regression:

$$z_t = a_t + \gamma_t \cdot \log(t) + u_t \tag{6}$$

with $a_t = a_1 + (a_2 - a_1) \cdot \mathbb{I}(t > T_B)$ and $\gamma_t = \gamma_1 + (\gamma_2 - \gamma_1) \cdot \mathbb{I}(t > T_B)$. Displaying the results visually, one can clearly see the structural break in the intercept and slope coefficients a and γ (see Figure 5). Obviously, the fit is noticeably improved. We take the obvious turning point in May 2019 as the break point T_B.[7]

[7] We confirm this trend break by running a Chow test which results in a highly significant F-statistic of 95.615

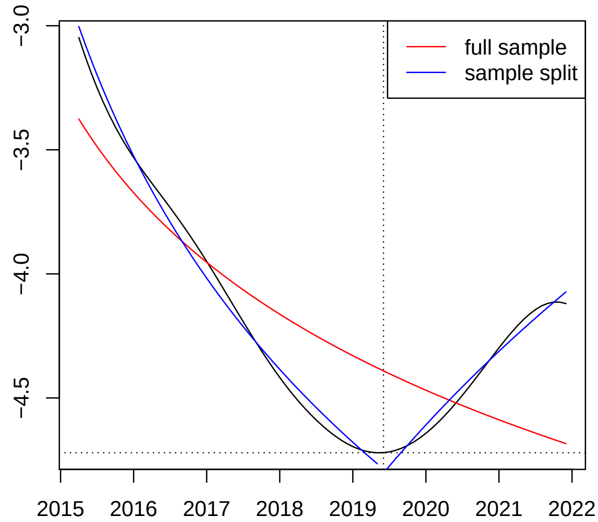

Figure 5: Fitted log trend lines with and without considering T_B

We proceed by re-applying the convergence tests and clustering procedures for sub-samples prior and after the breakpoint. For the sample running from August 2013 to May 2019, we reject the hypothesis of convergence for the complete panel and instead, we identify four different convergence clubs. The first club still consists of the two co-divergent countries Brazil and China. In the second club are Thailand, Hong Kong, South Africa, Malaysia, Japan, South Korea, Indonesia, Russia, Australia and United Kingdom. In the third club are Canada, India and United States, while in the last club are Switzerland, Sweden and Taiwan. The Clubs 2-4 show individually relative convergence. For the post trend break period (June 2019 to December 2021), we cannot reject the convergence hypothesis for all 18 ESG indices which form one single convergence club. Since $\gamma_2 \geq 2$, we not only have relative convergence, but also level convergence (see Table 3). This underlines the importance of accounting for this structural break.

Club building results - pre trend-break					
	n	γ_1	$se(\gamma_1)$	t-stat	p-value
Club 1	2	1.993	1.367	1.458	0.928
Club 2	10	-0.013	0.079	-0.171	0.432
Club 3	3	0.541	0.204	2.650	0.996
Club 4	3	0.264	0.083	3.182	0.999
Club building results - post trend-break					
	n	γ_2	$se(\gamma_2)$	t-stat	p-value
Club 1	18	2.073	0.081	25.529	1.000

Table 3: Results of convergence analyses when considering T_B

How can the structural break in May 2019 be explained? In line with Choi and Varian (2012), Preis

with a p-value of 0.000.

et al. (2013), Dimpfl and Jank (2016) and Borup and Schütte (2022), we investigate the Google Trends data for ESG. Preis et al. (2013) have illustrated that Google Trends data serve as an adequate proxy for trading volume. The worldwide ESG attention measure based on Google Trends is strongly increasing since 2018. Between 2018 and 2022, the search volume index has risen by more than 500% (see Figure 6). The measure reflects worldwide interest in ESG and strongly co-moves with related search queries (e.g., ESG investing and MSCI ESG). Due to the fact that we cannot directly incorporate an explanatory variable as a driving force for the time-varying factor loadings, we aim at providing an explanation for the detected breakpoint. We do so by investigating the time series properties of the ESG attention measure. We find the measure to be mildly explosive with an autoregressive parameter of 1.02. A corresponding Dickey-Fuller test ($DF = 1.18 > -0.08$) is significant and the unit root hypothesis is rejected in favour of explosiveness. This result is further confirmed by SADF and GSADF-tests of Phillips et al. (2011) and Phillips et al. (2015). Hence, explosive worldwide interest in ESG investments might explain the structural change towards global convergence of ESG indices. Leading forces behind the higher attention for ESG are incentives and regulations of major organisations, like the European green deal.

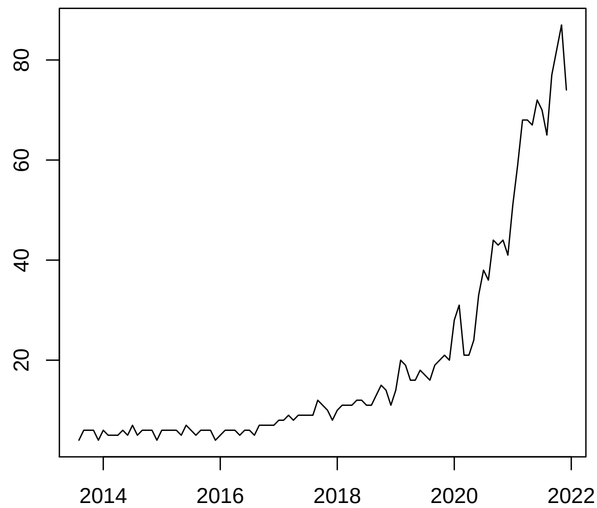

Figure 6: Google Trends intensity score for ESG

5 Discussion

We study the convergence behaviour of 18 different international ESG stock market indices. Our structural break analysis reveals insights beyond a full sample study. In particular, there is some heterogeneity in convergence prior to the break in May 2019 and even co-divergent behaviour among

Brazil and China. The post break period paints a rather different picture. We find that there is only one single convergence club in the post-period including all countries. On top of this, we find not only relative, but also level convergence. The structural break can be linked to the mildly explosive increasing investor attention to ESG investing which is proxied by using the Google Trends ESG intensity score. Thus, one implication of our study is that portfolio managers and other investment professionals as well as retail investors should be aware that currently there is less diversification between ESG indices than at the time in which this index category emerged. This can have major effects on the portfolio construction process. As a further research task it would be worthwhile to investigate if there is also a convergence behaviour in other asset categories which are formed based on ESG, i.e. fixed income investments (e.g., bonds and ETFs). It would also be of importance to compare the results to "non-ESG-compliant" investments by building own indices which show the development of non-ESG assets.

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