# Herding Behavior and the Dynamics of ESG Performance in the European

# **Banking Industry**

# Qishu Wang

Finance department, Seoul National University Business School, 1 Gwanak-ro, Gwanak-gu, Seoul, Korea 08826, Korea

#### ARTICLE INFO

JEL classification:

C23

C33

C58

G21

Q56

Keywords:

**ESG** 

European banking

Panel convergence

Phillip and Sul convergence method

#### ABSTRACT

We investigate the dynamics of ESG performance and explore the potential driving force, including the role of herd behavior among banks. Utilizing Phillips and Sul (2007)'s panel data convergence model and data from the 'EURO STOXX Banks index,' we identify a significant divergence in ESG performance followed by convergence towards separate clusters or clubs after 2018. Notably, Banks with lower Return on Equity (ROE) and leverage demonstrate herding tendencies towards improved ESG performance, emphasizing sustainability objectives and community ties. The study contributes to understanding the potential driving forces behind ESG convergence among EU banks.

#### 1. Introduction

In the last two decades, the European Union (EU) has relaxed financial service regulations to address inefficiencies. This deregulation has led to increased similarity and convergence in banking industries across the EU. Extensive research has been conducted on the European banking industry, highlighting the convergence tendencies (De Graeve et al., 2007; Vajanne, 2007; Gropp et al., 2014; Beccalli et al., 2003; Casu and Girardone, 2010), but also noting differences in ESG performance among major banks. This paper aims to investigate the dynamics of ESG performance convergence and explore the potential driving force, including the role of herd behavior among banks.

In the context of the growing attention to ESG, several previous studies have delved into convergence studies in this field. Gavrilakis and Floros (2023) focused on the European market and identified evidence of herding behavior in ESG stocks, highlighting the potential influence of ESG performance on stock market returns. However, within the banking sector, most studies have primarily explored its relationship with

general indicators such as market value, financial performance, or, at most, its impact on risk-taking behaviors (Di Tommaso and Thornton, 2020; Azmi et al., 2021; Ersoy et al., 2022; Galletta et al., 2023). Accordingly, our contribution aims to fill the gap left by prior literature by answering the following research question: Does herd behavior on ESG performance exist among main EU banks? If so, are there any implicit incentives driving herding behavior?

To examine this issue and its potential driving force, we employed Phillips and Sul's (2007, 2009) panel data convergence model on the main European banks, using the main banks in 'EURO STOXX Banks index' as the object for analysis. Phillips and Sul's approach extends the more classical cointegration framework commonly used for analyzing convergence. Early studies on stock market and interest rate convergence, particularly those conducted by Mylonidis and Kollias (2010), Sibbertsen et al., Rughoo and Sarantis (2014), have adopted this method. Recently, this methodology has also been applied to research on cryptocurrency and ESG (Apergis et al., 2021; Kerkemeier and Kruse-Beche, 2022).

Two main conclusions can be drawn from the analysis. First, there is a stronger and statistically significant divergence in the ESG performance of major European banks at the aggregate level after 2018, followed by convergence towards separate clusters or clubs. Second, clubs characterized by lower Return on Equity (ROE) and leverage demonstrate a propensity for herding towards better ESG performance. These banks prioritize sustainable practices to enhance their reputation, and stakeholder relationships, and mitigate risks, aligning with sustainability objectives and strengthening community ties.

In summary, we find evidence that banks with similar attributes follow a similar trajectory of ESG performance. Our results are broadly consistent with the literature on herding behavior due to payoff externality or conformity (Zwiebel, 1995) and reputation concerns (e.g., Scharfstein and Stein, 1990). As

Keynes stated, "it is better for reputation to fail conventionally than to succeed unconventionally" (see, for example, Devenow and Welch, 1996).

The structure is as follows: Section 2 describes the data with the methodology and the results are reported in Section 3. Concluding remarks are given in Section 4.

## 2. Data and methodology

#### 2.1 Data

We considered a sample of N = 20 major European banks from the 'EURO STOXX Banks index,' covering the period from 2009 to 2021 (T = 13), with data sourced from Refinitiv Datastream (Table 1). The collected dataset comprised yearly Environmental, Social, Governance scores, and a set of financial variables, namely size (total assets), leverage (measured as total debt % common equity) and Return on Equity.

The EURO STOXX Banks index includes major banks from Eurozone countries and is designed to track the overall performance of the banking sector in the region. As the index's focus is on the banking industry, it allows analyzing ESG performance convergence specifically. By comparing similar institutions, researchers can identify different herding tendencies in ESG practices specifically within this sector.

Table 1: Banks available in the EURO STOXX Banks Euro index

Bank	Country	Bank	Country
AIB GROUP	IRELAND	COMMERZBANK (XET)	GERMANY
BANCO BPM	ITALY	CREDIT AGRICOLE	FRANCE
BANCO DE SABADELL	SPAIN	DEUTSCHE BANK	GERMANY
BANCO SANTANDER	SPAIN	ERSTE GROUP BANK	AUSTRIA
BANK OF IRELAND GROUP	IRELAND	ING GROEP	NETHERLANDS
BANKINTER 'R'	SPAIN	INTESA SANPAOLO	ITALY
BBV.ARGENTARIA	SPAIN	KBC GROUP	BELGIUM
BNP PARIBAS	FRANCE	NORDEA BANK (HEL)	FINLAND
BPER BANCA	ITALY	SOCIETE GENERALE	FRANCE
CAIXABANK	SPAIN	UNICREDIT	ITALY

#### 2.2 Empirical methodology

We employ the well-established methodology of Phillips and Sul (2007, 2009) to investigate convergence and clustering in our study. This approach allows us to test whether there is convergence concerning the heterogeneous time-varying idiosyncratic components after controlling for a common growth component and identify convergence clubs and divergent units. Specifically, the method utilizes a log t regression test based on a nonlinear time-varying factor model. To begin, the time-varying factor are defined as:

$$X_{it} = \delta_{it}\mu_t$$

where i = 1, ..., N and t = 1, ..., T.  $X_{it}$  represents environmental, social and government scores, which are composed of a common component,  $\mu_t$ , and an idiosyncratic component,  $\delta_{it}$ , both of which are timevarying.  $\delta_{it}$  is a measure of the distance between  $X_{it}$  and the common component,  $\mu_t$ . Phillips and Sul (2007) defined the relative transition parameter,  $h_{it}$  as follows:

$$h_{it} = \frac{X_{it}}{\frac{1}{N} \sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{\frac{1}{N} \sum_{i=1}^{N} \delta_{it}}$$

In the context of convergence, every panel unit must reach a common limit in their transitions, denoted as,  $h_{it} \rightarrow 1 \ \forall i = 1, ..., N$ , as  $t \rightarrow \infty$ . For the cross-sectional variance  $H_t$  it holds:

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

Phillips and Sul (2007, 2009) also presented the semi-parametric form of  $\delta_{it}$  as:

$$\delta_{it} = \delta_i + \frac{\sigma_i \xi_{it}}{L(t)t^{\alpha}}$$

Here,  $\delta_i$  represents an individual-specific component, while  $\sigma_i$  serves a scaling factor and  $\xi_{it}$  is an error term which is i.i.d. (0,1) across i. L(t) is a slowly varying function and  $\alpha$  is the decay rate (convergence rate). The null hypothesis of convergence  $H_c$  and the alternative of divergence  $H_D$  are given as:

$$H_c: \delta_i = \delta$$
 and  $\alpha \ge 0$ ,

$$H_D: \delta_i \neq \delta \ \forall \ i \ \text{or} \ \alpha < 0$$

To perform the hypothesis test, the following OLS log t regression can be used:

$$\log\left(\frac{H_1}{H_t}\right) - 2\log L(t) = \hat{a} + \hat{b}\log t + \varepsilon_t$$

where for t = rT, rT+1, ..., T where r > 0 set on the interval [0.2, 0.3]. Based on Monte Carlo experiments, it is observed that setting "r" within [0.2, 0.3] yields satisfactory results. Specifically, it is recommended to choose "r = 0.3" for small or moderate sample sizes "T" ( $\leq 50$ ) and "r = 0.2" for large sample sizes "T" ( $\geq 100$ ).  $H_1$  and  $H_t$  represent the sample analogs of the unconditional and conditional variances of the factor,  $\hat{a}$  and  $\hat{b}$  are coefficients to be estimated. For  $\hat{b} = 2\hat{a}$ , the null hypothesis is considered a one-sided test of  $\hat{b} \geq 0$  against  $\hat{b} < 0$ . If  $\hat{b} \geq 2$  ( $\alpha \geq 1$ ), there is level convergence, while if  $0 \leq \hat{b} < 2$  ( $0 \leq \hat{a} < 1$ ), there is only relative convergence. In contrast, for  $\hat{b} < 0$ , there is divergence.

Then, we apply Phillips and Sul's (2007, 2009) clustering algorithm to identify distinct convergence and divergence clubs as follows:

- 1. Cross-Section Sorting: The banks within the panel are arranged in descending order based on their  $X_{it}$  panel units from the last period.
- 2. Group Information: To identify a core group, the log-t regression model is sequentially performed for the k highest member banks using the cut-off point criterion:  $k^* = ArgMax_k\{t_{\hat{b}_k}\}$ , with the condition  $Min_k\{t_{\hat{b}_k}\} > 1.65$ , for k = 2, 3, ...N. Then, add each remaining unit one at a time and reestimate log-t regression model. If  $\hat{b} > 0$ , a new unit is added to the convergence club. All these units build the first convergence club.
- 3. Recursion and Stopping Criteria: The above steps are repeated iteratively for the remaining banks until convergence clubs can no longer be formed (if  $t_{\hat{b}_k} \le -1.65$ ). As a result of this iterative approach, each formed club is associated with its own convergence path.

#### 3. Empirical results

Initially, we commence our analysis by scrutinizing the Google Trends data concerning ESG topics.

Notably, prior investigations by Preis et al. (2013) have established the suitability of Google Trends data as

a dependable indicator of trading volume. The dynamic in Figure 1 reveals a conspicuous upward trend in the global measure of ESG attention, commencing from 2018 and extending beyond. Specifically, the search volume index has experienced a substantial increase of over 5 times during the period from 2018 to 2022.



Figure 1: Google Trends intensity score for ESG from 2014 to 2023

By applying the aforementioned methodology to assess the ESG scores of the main European banks, we employed a clustering algorithm to identify distinct convergence clubs based on ESG scores. Across all three pillars, we found that the null hypotheses of convergence are rejected at the 5% significance level (refer to Table 2). In particular, stronger clustering convergence tendencies can be observed in the social and governance performance domain. This inference primarily rests upon two fundamental reasons. First, when comparing the convergence test results for the three pillars in the full sample, the results for social and governance scores show a greater tendency to reject the null hypothesis, yielding t-statistics of -73.4589 and -86.3617, respectively. Second, within club 3, clustered based on social scores, the speed of convergence, b of 0.6822 with a t-statistic of 0.5205, which failed to reject the null hypothesis of convergence, indicating a relatively high level of convergence. Similarly, with regard to government scores, club 1 also demonstrated relatively evident herd behavior, as evidenced by its clustering coefficient of 0.4606.

Table 2: Results of environmental scores' convergence test

Convergence test without clustering	n	b	se(b)	t-stat
Club 1	20	-1.7537	0.3755	-4.6702

# Convergence test with clustering

Subgroup	Banks	n	b	se(b)	t-stat
	BANCO BPM, BANCO SANTANDER,				
	BBV.ARGENTARIA, BNP PARIBAS,				
Club 1	COMMERZBANK (XET), CREDIT AGRICOLE,	11	-0.0517	0.1786	-0.2896
	DEUTSCHE BANK, INTESA SANPAOLO, KBC				
	GROUP, SOCIETE GENERALE, UNICREDIT				
Club 2	BANCO DE SABADELL, BANKINTER 'R', BPER BANCA, CAIXABANK, ING GROEP	5	-0.4746	0.6073	-0.7815
Club 3	ERSTE GROUP BANK, NORDEA BANK (HEL)	2	-0.0034	1.1758	-0.0029
non-convergence group	AIB GROUP, BANK OF IRELAND GROUP	2	-1.203	0.2124	-5.6626
Results of social scores	d'appyargence test				
			h	gg(h)	t stat
Convergence test without	at clustering	$\frac{n}{20}$	b	<i>se</i> (b)	<i>t</i> -stat
Club 1		20	-1.461	0.0199	-73.4589
Convergence test with c	lustering				
Subgroup	Banks	n	b	<i>se</i> (b)	t-stat
Club 1	AIB GROUP, BANCO DE SABADELL, BANCO SANTANDER, BNP PARIBAS, CAIXABANK,	6	-0.1827	0.1597	-1.1445
	DEUTSCHE BANK (XET)				
	BANCO BPM, BANK OF IRELAND GROUP,				
Club 2	BANKINTER 'R', BBV.ARGENTARIA, BPER BANCA,	9	-0.1044	0.2618	-0.3989
Club 2	COMMERZBANK (XET), ERSTE GROUP BANK, KBC GROUP, SOCIETE GENERALE	9	-0.1044	0.2018	-0.3369
Club 3	CREDIT AGRICOLE, ING GROEP, NORDEA BANK	4	0.6822	1.3106	0.5205
	(HEL), UNICREDIT				
non-convergence group	INTESA SANPAOLO	1	-	-	-
Results of governance	scores' convergence test				
Convergence test without	at clustering	n	b	se(b)	t-stat
Club 1		20	-1.669	0.0193	-86.3617
Convergence test with c	lustering				
Subgroup	Banks	n	b	<i>se</i> (b)	t-stat
	AIB GROUP, BANCO BPM, BANCO DE SABADELL,				
	BANCO SANTANDER, BANKINTER 'R',				
Club 1	BBV.ARGENTARIA, BNP PARIBAS, CAIXABANK,				
	COMMERZBANK (XET), DEUTSCHE BANK (XET),	16	0.4606	0.6161	0.7476
	ERSTE GROUP BANK, ING GROEP, INTESA				
	SANPAOLO, NORDEA BANK (HEL), SOCIETE GENERALE, UNICREDIT				
Club 2	BANK OF IRELAND GROUP, CREDIT AGRICOLE	2	-1.0857	1.1731	-0.9254
non-convergence groun	BPER BANCA, KBC GROUP	2	-2.4757	0.6981	-3.5463
non-convergence group	BYEK BANCA, KBC GRUUP	2	-2.4/5/	0.6981	-3.54

In Figure 2, we present the moving curves of ESG scores for the main European banks on the 'EURO STOXX Banks index.' From an environmental perspective, the trend of clustering changes becomes stronger after 2018. Moreover, we can observe that from club 1 to club 3, the environmental scores show a herding trend. The final clustering point of club 1 is concentrated around 90 points, while club 2 and club 3 are concentrated below 90 and below 80 points, respectively. Similar to environmental clubs, social clubs also show a trend of herding behavior, especially after 2018. The final clustering point of club 2 is around 80 points, while club 3 is around 70 points. Regarding governance factors, most European banks are in club 1, with a significant catch-up trend after 2017-2018. However, banks like BANK OF IRELAND GROUP, CREDIT AGRICOLE, BPER BANCA, and KBC GROUP, with poor governance performance, remain in club 2 and the non-convergence group, showing stagnant development in their corporate governance.

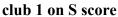
The EU banking sector experienced significant divergence in ESG performance clustering after 2018, influenced by factors such as strengthened regulations, market forces, and investor preferences. Policy guidance, such as the Sustainable Finance Action Plan launched in 2018, EU Taxonomy Regulation in 2020, and the implementation of the EU Sustainable Finance Disclosure Regulation (SFDR) in March 2021, played a crucial role in shaping the ESG landscape. In the face of these policy impacts, different types of banks respond differently. The differences among banks in the same club seem to decrease over time, whereas those between clubs seem to grow larger. We interpret our results to be broadly consistent with the hypothesis of herding behavior of EU banks in terms of ESG performance due to reputational concerns or conformity (Scharfstein and Stein, 1990; Zwiebel, 1995). We argue that these are powerful economic forces, even in the context of the European banking sector. Such convergence and divergence among different participants are often observed in other economic contexts, such as financial analysts (e.g., Hong and Solomon, 2000).

Banks that have historically demonstrated strong conventional practices and compliance with traditional financial metrics may be more cautious in adopting unconventional or more progressive ESG strategies. These banks might fear potential reputational risks or negative market reactions associated with principalagent problems. Conversely, banks that have historically underperformed in conventional financial metrics might be more willing to adopt unconventional ESG practices as a way to improve their reputation and demonstrate a commitment to sustainability. This could be a strategic move to differentiate themselves from their peers and attract socially responsible investors or stakeholders.

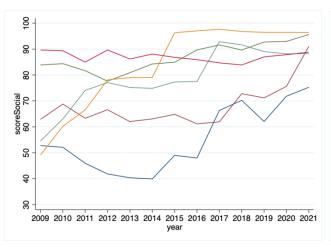
Figure 2: A. Moving curves of E scores non-convergence club on E score club 1 on E score 100 8 8 8 80 scoreEniviromental 50 60 70 scoreEnivirom 50 60 9 4 30 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 club 3 on E score club 2 on E score 9 9 8 8 8 80 scoreEniviromental 50 60 70 scoreEniviromental 50 60 70 4 4 30 8 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021

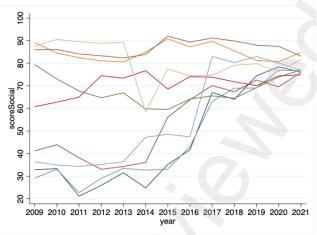
2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021

Figure 2: B. Moving curves of S scores



### club 2 on S score





### club 3 on S score

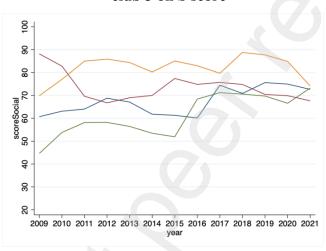
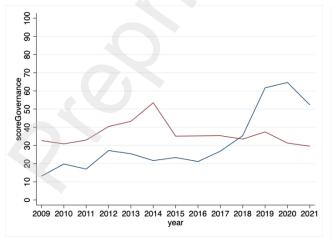
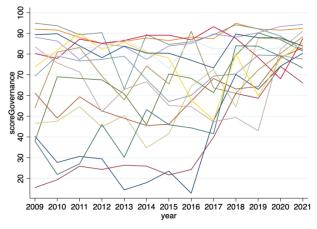


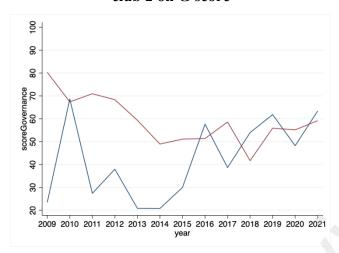
Figure 2: C. Moving curves of G scores non-convergence club on G score

club 1 on G score





club 2 on G score



To further validate this hypothesis, we continuously investigate the underlying factors driving the observed clustering trend. We conducted a series of one-way analysis-of-variance (ANOVA) tests on dominant financial ratios, as shown in Table 3. The results indicate a clear tendency for herding based on increasing Return on Equity (ROE) and leverage. Since the club rankings are arranged in descending order of ESG scores, groups with lower ROE and leverage demonstrate a stronger inclination for ESG development. Additionally, larger-sized groups exhibit herding behavior, particularly concerning social and environmental aspects, in pursuit of better ESG performance.

In the banking industry, reputation is crucial for gaining stakeholder trust and attracting business. Banks with lower ROE and leverage may face challenges in achieving conventional financial success, leading to negative perceptions from investors, customers, and regulators. To protect their reputation, they may need to explore unconventional approaches to success. Thus, developing ESG practices offers these banks an opportunity to differentiate themselves and thrive unconventionally. Prioritizing sustainability, social responsibility, and ethical governance signals their commitment to long-term viability and aligning their operations with broader societal interests. This commitment can help rebuild their reputation and position them as responsible and forward-thinking institutions. In contrast, 'good' banks characterized by relatively higher ROE and high leverage, indicative of commendable performance in conventional metrics, tend to

allocate less focus toward ESG performance. Such banks may harbor apprehensions regarding potential reputational risks or adverse market reactions arising due to principal-agent conflicts.

Table 3: one-way analysis-of-variance on dominant financial ratios between ESG clubs

		L	N (total assets)		Leverage		ROE
	club	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
	1	20.504347	0.78038967	478.75031	136.69905	-6.0992309	6.8452377
E score clubs	2	19.061309	0.99155827	467.5985	121.8042	3.6855244	3.7497886
	3	19.72629	0.48867359	599.38666	174.53859	6.7413846	2.0812737
		L	N (total assets)		Leverage		ROE
	club	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
	1	20.103367	1.1607298	405.38694	107.05976	1.9441025	7.0203286
S score clubs	2	19.310868	0.94757056	463.82232	131.11345	4.6728205	3.9804022
	3	20.690221	0.37945258	603.28667	150.41018	4.823077	4.5980343
		L	N (total assets)		Leverage		ROE
	club	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
C	1	20.00069	1.0022986	482.38479	137.1914	3.6934135	5.6571239
G score clubs	2	20.004443	1.2734378	502.12167	187.67196	2.1265385	1.543434

## 4. Concluding remarks

Our study investigates the dynamics of ESG performance among major EU banks, exploring the question of whether herd behavior exists in their ESG performance. The analysis reveals a significant divergence in their ESG performance at the aggregate level after 2018, followed by herd behavior towards distinct clusters.

Another implication of our study is that banks with lower ROE and leverage exhibit herding behavior towards better ESG performance, emphasizing sustainable practices to enhance reputation and stakeholder relationships, and mitigate risks, aligning with sustainability objectives. As a further research task, it would be worthwhile to explore the specific factors driving ESG performance herding among major EU banks post-2018. In this regard, investigating the impact of different regulatory frameworks, market forces, and transparency practices on banks' ESG herding patterns may provide valuable insights. Furthermore, studying the long-term effects of ESG herding on banks' financial stability and market positioning could also contribute to a comprehensive understanding of ESG integration in the European banking industry.

# Acknowledgements

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

#### References

Apergis, N., Koutmos, D. and Payne, J.E. (2021) 'Convergence in cryptocurrency prices? The role of market microstructure', Finance Research Letters, 40, p. 101685. doi:10.1016/j.frl.2020.101685.

Azmi, W. et al. (2021) 'ESG activities and Banking Performance: International Evidence from Emerging Economies', Journal of International Financial Markets, Institutions and Money, 70, p. 101277. doi:10.1016/j.intfin.2020.101277.

Beccalli, E., Casu, B. and Girardone, C. (2003a) 'Efficiency and stock performance in European banking', SSRN Electronic Journal [Preprint]. doi:10.2139/ssrn.391668.

Beccalli, E., Casu, B. and Girardone, C. (2003b) 'Efficiency and stock performance in European banking', SSRN Electronic Journal [Preprint]. doi:10.2139/ssrn.391668.

Casu, B. and Girardone, C. (2010) 'Integration and efficiency convergence in EU banking markets', Omega, 38(5), pp. 260–267. doi:10.1016/j.omega.2009.08.004.

De Graeve, F., De Jonghe, O. and Vennet, R.V. (2007) 'Competition, transmission and bank pricing policies: Evidence from Belgian loan and Deposit Markets', Journal of Banking & Finance, 31(1), pp. 259–278. doi:10.1016/j.jbankfin.2006.03.003.

Devenow, A. and Welch, I. (1996a) 'Rational herding in Financial Economics', *European Economic Review*, 40(3–5), pp. 603–615. doi:10.1016/0014-2921(95)00073-9.

Di Tommaso, C. and Thornton, J. (2020) 'Do ESG scores effect bank risk taking and value? evidence from European banks', Corporate Social Responsibility and Environmental Management, 27(5), pp. 2286–2298. doi:10.1002/csr.1964.

Ersoy, E. et al. (2022) 'The impact of ESG scores on Bank Market Value? evidence from the U.S. Banking Industry', Sustainability, 14(15), p. 9527. doi:10.3390/su14159527.

Galletta, S. and Mazzù, S. (2022) 'ESG controversies and Bank Risk Taking', Business Strategy and the Environment, 32(1), pp. 274–288. doi:10.1002/bse.3129.

Gavrilakis, N. and Floros, C. (2023) 'ESG performance, Herding Behavior and Stock Market Returns: Evidence from Europe', Operational Research, 23(1). doi:10.1007/s12351-023-00745-1.

Gropp, R., Kok, C. and Lichtenberger, J.-D. (2014) 'The dynamics of bank spreads and financial structure', Quarterly Journal of Finance, 04(04), p. 1450014. doi:10.1142/s2010139214500141.

Hong, H., Kubik, J.D. and Solomon, A. (2000) 'Security analysts' career concerns and herding of earnings forecasts', The RAND Journal of Economics, 31(1), p. 121. doi:10.2307/2601032.

Kerkemeier, M. and Kruse-Becher, R. (2022) 'Join the club! dynamics of global ESG indices convergence', Finance Research Letters, 49, p. 103085. doi:10.1016/j.frl.2022.103085.

Mylonidis, N. and Kollias, C. (2010) 'Dynamic European Stock Market Convergence: Evidence from Rolling Cointegration Analysis in the first Euro-Decade', Journal of Banking & Finance, 34(9), pp. 2056–2064. doi:10.1016/j.jbankfin.2010.01.012.

Phillips, P.C. and Sul, D. (2007) 'Transition modeling and econometric convergence tests', Econometrica, 75(6), pp. 1771–1855. doi:10.1111/j.1468-0262.2007.00811.x.

Phillips, P.C. and Sul, D. (2009) 'Economic transition and growth', Journal of Applied Econometrics, 24(7), pp. 1153–1185. doi:10.1002/jae.1080.

Preis, T., Moat, H.S. and Stanley, H.E. (2013) 'Quantifying trading behavior in financial markets using google trends', Scientific Reports, 3(1). doi:10.1038/srep01684.

Rughoo, A. and Sarantis, N. (2014) 'The global financial crisis and integration in European retail banking', Journal of Banking & Finance, 40, pp. 28–41. doi:10.1016/j.jbankfin.2013.11.017.

Scharfstein, D. S., & Stein, J. C. (1990). Herd Behavior and Investment. The American Economic Review, 80(3), 465–479. http://www.jstor.org/stable/2006678

Sibbertsen, P., Wegener, C. and Basse, T. (2014) 'Testing for a break in the persistence in yield spreads of Emu Government bonds', Journal of Banking & Finance, 41, pp. 109–118. doi:10.1016/j.jbankfin.2014.01.003.

Vajanne, L. (2008) 'Integration in euro area retail banking markets - convergence of credit interest rates', SSRN Electronic Journal [Preprint]. doi:10.2139/ssrn.1081564.

Zwiebel, J. (1995) 'Corporate conservatism and relative compensation', Journal of Political Economy, 103(1), pp. 1–25. doi:10.1086/261973.