ESG VERSUS FINANCIAL PERFORMANCE OF LARGE CAP FIRMS: THE CASE OF EU, U.S., AUSTRALIA AND SOUTH-EAST ASIA

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Summary

A long-standing question in investment management is whether investing in firms that score highly on sustainability issues leads to lower returns of the investment portfolio, and no consensus on that matter has been reached yet. We investigate this issue by looking at the relationships between Refinitiv combined ESG (Environmental, Social and Governance) scores for large cap firms and their financial performance. In particular, we address the question how the stock returns, market value and volatility of large cap firms in 4 regions – the EU, the U.S., Australia and Asia (Japan, China and South Korea), are related to their ESG performance.

ESG data availability has increased significantly in the last few years, especially for Asian region. Using correlation analysis, we observe that ESG performance is strongly correlated with firm's size, larger companies have on average better ESG scores. This must be considered when implementing ESG criteria in investment strategies, as improving ESG scores of a portfolio can introduce an (undesired) size effect and tilt the portfolio towards larger firms.

Using robust panel data methodology and an extensive dataset spanning over 2,000 companies and 9 years, we show that the investors in the EU and Australian firms do not sacrifice their returns by investing in highly ESG scoring firms. This is arguably a result of the EU and Australia leading institutional investors' embrace of ESG, and actively incorporating sustainability in their portfolio management considerations.

For the U.S. and Asian companies, where sustainability issues are not as high on investors' agenda, a firm's ESG performance tends to have negative relationship to its stock returns. However, also in these regions, there is a benefit in investing in highly ESG-scoring firms, as these are shown to have lower volatility (and hence, to be less risky). Furthermore, we see that more sustainable firms had higher resilience and lower losses during the recent COVID-19 pandemic.

Introduction

Sustainable investing is the buzzword in the modern investment management. Tomorrow's investors – millennials – are more committed to sustainability and make more environmentally aware choices than any of the previous generations. This is highlighted in a study of Morgan Stanley's Institute for Sustainable Investing (MS (2017)), which summarizes these effects in the investment industry.

While the intentions of investors are clear, incorporating sustainability in investment management remains challenging. Alongside traditional expected return and volatility, an additional performance measure should be added to assess quality of investment portfolios.

Sustainability, or rather ESG performance of a firm is a concept that encompasses many dimensions. Environmental issues include, for example, emissions and waste management, social performance might include workforce diversity and community involvement, and governance measures incorporate stakeholder engagement and share voting rights. Given the broad nature of ESG, it is challenging to measure all these aspects and express them in just a few numbers.

ESG data is becoming increasingly available from data providers such as Refinitiv. ESG-related information is collected for a vast range of companies, and this process combines a vast number of information sources and cutting-edge analytics to extract ESG-related information from those sources. Refinitiv ESG scores are the industry standard database that reflect official company disclosure on environmental, social, and governance metrics.

ESG and financial performance of firms is currently a hot topic in investment management and academic research. To assess the relationship between ESG and financial performance of a firm, the techniques range from a simple correlation or regression analysis of companies' returns vs. their ESG scores to the classical Fama-French three-factor model or its extended versions.

In earlier studies, the evidence for a relationship between ESG performance and stock returns is mixed. Early studies claimed that more "sustainable" or "socially responsible" firms had significantly lower returns than the market benchmark. However, there are also numerous studies that find that socially responsible funds and stocks outperform their peers.

A meta-analysis on this topic was carried out by Revelli and Viviani (2015). The authors consider 85 different studies in a 20-year time frame and conclude that there is no significant relationship between ESG and stock performance based on these 85 studies. This is confirmed by many recent papers on this subject.

In all, it seems that the current consensus in academic community is that there is no significant relationship between ESG and financial performance. The investment community, however, is split into two camps: believers that ESG comes at a cost of financial returns and those who believe that good ESG performance guarantees better returns (and lower risk) in the future.

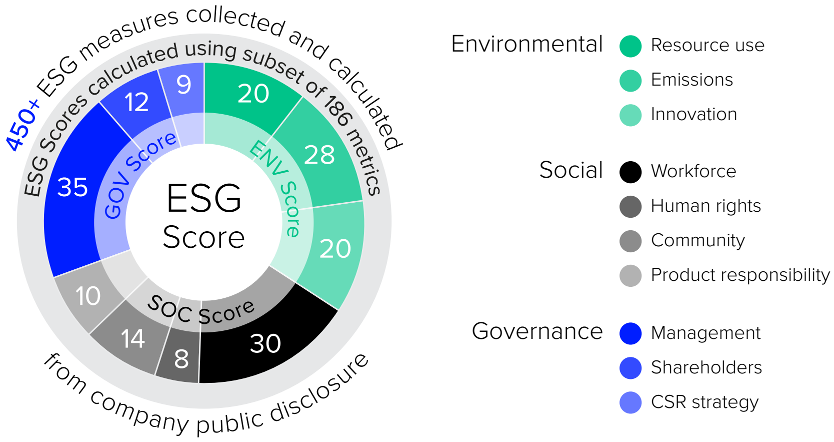
Most of the existing studies on the relationship between ESG performance and stock returns are limited to U.S. firms. Here we take a broader approach: we look at the ESG vs. financial performance of firms across many developed markets, such as EU, Australia and South-East Asia. We place ESG in the framework of well-known statistical models that aim to explain a firm's stock returns as a function of many variables, such as firm's size and its financial ratios. We also investigate how the ESG data quality differs per region and reporting period, and how financial characteristics other than stock returns are related to ESG scores.

ESG data and its availability for different regions

Our source of ESG data is Refinitiv combined ESG scores which take controversy scores into consideration. These scores are currently available for 9,000 stocks (which together represent approximately 80% of global market cap).

For each covered company, Refinitiv collects over 450 ESG-related metrics which are divided into three categories and ten subcategories. The categories are Environment (E), Social (S) and Governance (G). Of all the available variables, 186 are used to create E, S, G and the overall ESG scores. How these variables are allocated among the available subcategories is shown in Figure 1.

Figure 1: Overview of categories and subcategories in Refinitiv ESG data



We use yearly ESG scores, as this is the typical scores' update frequency (although for some subcategories the scores are updated more frequently). We do not do our analysis separately for E, S and G scores but use the overall Refinitiv combined ESG scores – the more detailed analysis per category can be provided upon request.

The stock universe is the set of constituents of the S&P 500, STOXX 600, Australia ASX 300, Japan Nikkei 500, China A-share and South Korea KOR 200 indices, which together encompass over 2,000 large cap firms. The time period we consider is from 2010 to 2018[1] - the period during which ESG measurements have become increasingly available (more about this later). Companies for which the majority of combined ESG scores are available and that trade more than 125 days a year are included. Thus, the actual number of companies that we use in our analysis is less than the number of all constituents (more detail can found in Table 4 in Appendix A). Company-specific characteristics (such as their financial ratios) are retrieved from Refinitiv Datastream.

ESG data availability and quality have improved significantly during the last decade.

Region	% of companies without ESG score – 2012	% of companies without ESG score – 2018
EU	25%	7%
U.S.	20%	2%
Australia	50%	20%
Japan	30%	20%
South Korea	60%	40%

For Chinese firms, there is an explosion of ESG reporting in the last two years: in 2017 and 2018 three times more Chinese firms have ESG scores available than before 2017. This underlies the well-known positive trend in recent sustainability awareness of Chinese firms.

1 Till the publication date of this paper, ESG scores for 2019 were not available at time of research.

Methodology

First, we explore the relationship between the firms' ESG scores, returns, volatilities and size by means of correlations, which already give us some interesting insights. Furthermore, we find more sound empirical evidence through regression. For that, we treat companies as individuals, observed through time. This leads to a panel data approach, where the individual company characteristics as well as their ESG score may explain their stock returns. For details of our panel data regressions, we refer to the Appendix.

In our panel regression model, the dependent variable is the cumulative excess return $\boldsymbol{ER}_{it}$ of the stock i in year $\boldsymbol{t}$, inclusive of dividends, over the risk free rate. For U.S. and EU stocks, we adopt the 1–month Libor rate in U.S. dollars and 1–month Euribor rate in Euros, respectively.

As Libor-like rates are not calculated for Australia, China and South Korea, for these countries we employ 1-year government bond yield in local currency as the risk free rate, as well as for Japan.

The determinants of the excess return for a stock, apart from its ESG score, are those financial variables found to be significant in other studies, e.g., that of Bauer et al. (2004):

(i) Size: $\boldsymbol{MV}_{it}$ (Market Value of stock $\boldsymbol{i}$ relative to the market value of all stocks in a country at time $\boldsymbol{t}$)

(ii) Cash flow-to-price ratio: $\boldsymbol{CP}_{it}$

(iii) Book-to-price ratio: $\boldsymbol{BP}_{it}$

(iv) Stock volatility: $\boldsymbol{Var}_{it}$ (annualized variance of stock $\boldsymbol{i}$ return in year $\boldsymbol{t}$).

Since ESG scores are predominantly constant over a given year, other variables should be also measured per year. To achieve that, we average the size and ratios over each year. ESG scores are expressed as decimals rather than percent (so they are divided by 100), to share the same magnitude as other independent variables. To obtain a balanced panel data set, we only include those stocks with all explanatory variables available.

The panel data regression model is:

$$\boldsymbol{ER}_{it} = \boldsymbol{\alpha}_i + \boldsymbol{\beta}_1\boldsymbol{MV}_{it} + \boldsymbol{\beta}_2\boldsymbol{Var}_{it} + \boldsymbol{\beta}_3\boldsymbol{CP}_{it} + \boldsymbol{\beta}_4\boldsymbol{BP}_{it} + \boldsymbol{\beta}_5\boldsymbol{ESG}_{i,t-1} + \boldsymbol{\varepsilon}_{it} \qquad (1)$$

and it is estimated separately for stocks in 4 regions. Table 5 in Appendix A presents the summary statistics of all variables for the balanced panel data set.

Results

In this section, we report the results of our analysis: the relationships between firms' combined ESG scores and the next year cumulative excess returns, market values and volatilities, for all four regions we consider. We show correlation graphs, the results of the panel data model summarizing the effects of the ESG scores on cumulative excess returns and discuss these re- sults.

Firm characteristics vs ESG scores

Figure 2 shows, per year, the correlations between the ESG scores, market values, annual excess returns and volatilities for all stocks in the U.S. and EU. Figure 3 shows the same information for Australia and Asia.

Overall, the cross-section correlation patterns shown in Figure 2 and Figure 3 are similar for all regions. The most pronounced effect is that the correlations between the ESG score and market value (i.e., the size of a company) are positive and significant for all years and all regions. This shows that larger firms tend to exhibit better ESG performance, as they have more means to invest in sustainability issues and hence improve their ESG scores. For firms in all 4 regions, we also observe significant negative correlations between the ESG score and return volatility of returns, suggesting that the returns of highly ESG scoring firms tend to have lower volatility, indicating that more sustainable firms tend to have more consistent and less volatile financial performance.

Note that here we did not control for any additional determinants of excess returns, and neither we have considered time-varying effects - issues that we addressed properly when we applied a panel data model, whose results are summarized below.

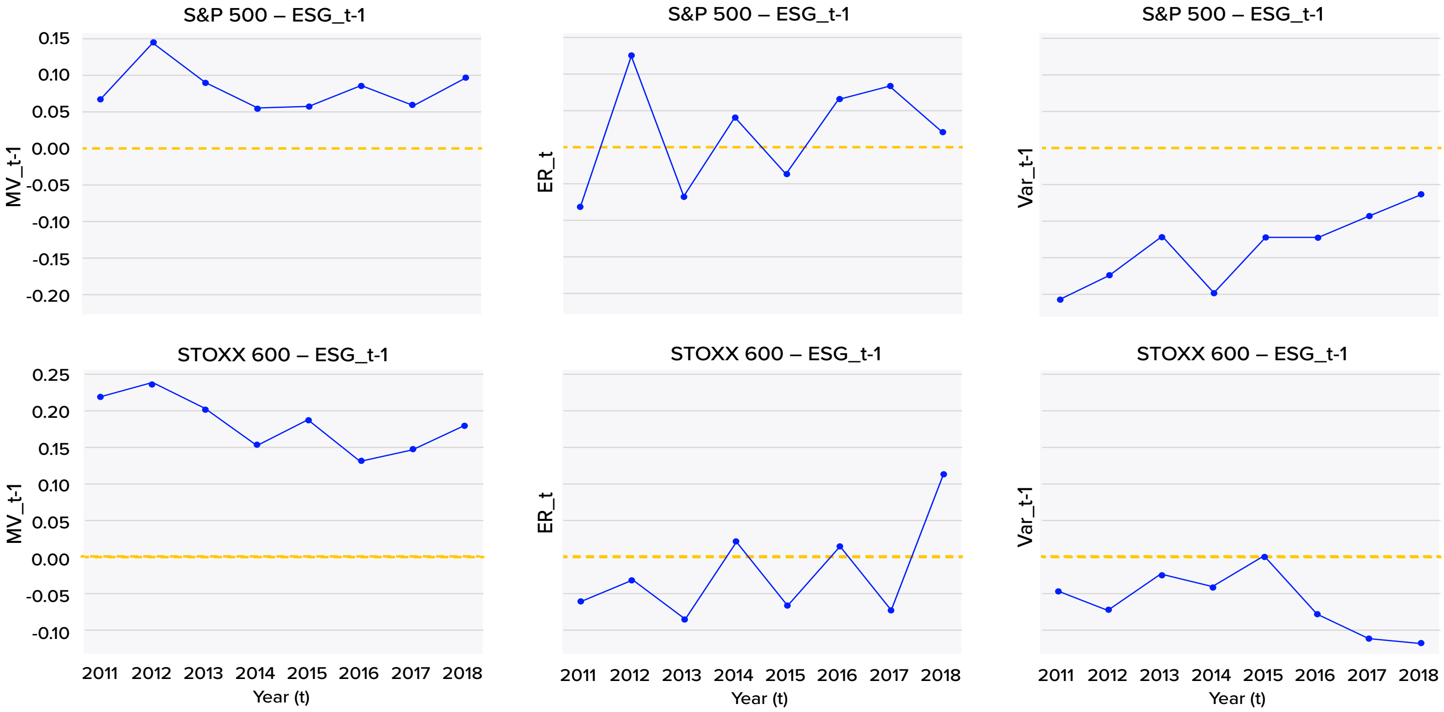


Figure 2: Yearly correlations between the ESG scores and firm's characteristics, U.S. and EU.

Figure 3: Yearly correlations between the combined ESG scores and firm's characteristics, Australia and Asia.

Results of the panel data model estimation

Table 2 presents the estimation results of the model (1) for stocks in S&P 500 and STOXX 600 indices, and Table 3 reports the estimation results for stocks in Australia and Asia[2].

EU stocks with higher ESG scores do not compromise (but in fact, enhance) the returns, as the corresponding regression coefficient is positive and significant at 10% level. As a side remark, we observe that, for EU firms, there is a significant negative relationship between the market value and the excess return, suggesting that smaller EU companies generate higher returns on average. Similar to EU firms, highly ESG scoring firms in Australia do not sacrifice their stock returns as for those firms we do not observe a significant relationship between ESG scores and returns.

For U.S. firms, the significant determinants of excess returns are volatility (indicating the well- known low vol effect) and the ESG score, which both have a significant negative relationship. This is arguably a result of less focus on sustainability in the U.S., leading to lower (than in EU) demand by investors for stocks of highly ESG scoring firms. In Asia, where sustainability issues only recently coming to investors' attention, the situation is similar to the U.S.: Asian firms are more alike to U.S. ones as the highly ESG scoring firms tend to have lower next year returns. Contrary to the U.S., Asian companies of smaller size and higher volatility are more likely to generate higher returns.

2 The Haussman test indicated that a Fixed Effect model is more appropriate than the Random Effect model for all regions (except Australia, where both models performed equally well).

As a robustness check, we perform the same panel data model estimation for stocks in Japan, China and South Korea separately (the results are in Appendix A). For Japan and China, ESG scores are negatively related to returns, while in South Korea, the relationship between ESG scores and excess returns is insignificant. Thus, we see that the results for individual Asian countries are broadly in line with the results for the region as a whole, South Korean firms being the exception. So if an investor wants to diversify her portfolio by including Asian firms, South Korean firms are currently better candidates if sustainability issues are involved.

Table 2: Panel regression model estimates, U.S. and EU

	S&P 500					STOXX 600				
	MV	Var	CP	BP	ESG	MV	Var	CP	BP	ESG
coeff.	-1,914	**-0,528**	0,059	-0,018	**-0,747**	**-18,886**	-0,386	-0,017	-0,015	0,079
sd.	4,305	0,223	0,137	0,030	0,057	6,860	0,396	0,046	0,035	0,062
t stat.	-0,445	-2,369	0,427	-0,609	-13,134	-2,753	-0,975	-0,379	-0,438	1,271
p	0,657	0,018	0,669	0,543	0,000	0,006	0,329	0,704	0,662	0,104
Haussman stat.			170.545					28.784		
pH			0,000					0,000		

Significant coefficients at 5% level are in boldface.
The standard deviation, t statistic and p value are calculated by panel-robust estimation.
The Haussman statistic is panel-robust and obtained by 3000 bootstrap samples.

Table 3: Panel regression model estimates, Australia and Asia

	Australia - RE estimates					Asia - FE estimates				
	MV	Var	CP	BP	ESG	MV	Var	CP	BP	ESG
coeff.	-0,491	**0,656**	0,696	**-0,183**	**0,036**	**-8,169**	**0,614**	0,206	-0,020	**-0,421**
sd.	0,419	0,140	0,355	0,077	0,058	4,126	0,140	0,120	0,049	0,080
t stat.	-1,172	4,674	1,960	-2,364	0,622	-1,980	4,376	1,712	-0,407	-5,242
p	0,242	0,000	0,050	0,018	0,534	0,048	0,000	0,087	0,684	0,000
Haussman stat.			4.150					47.030		
pH			0.528					0,000		

Significant coefficients at 5% level are in boldface.
The standard deviation, t statistic and p value are calculated by panel-robust estimation.
The Haussman statistic is panel-robust and obtained by 3000 bootstrap samples.

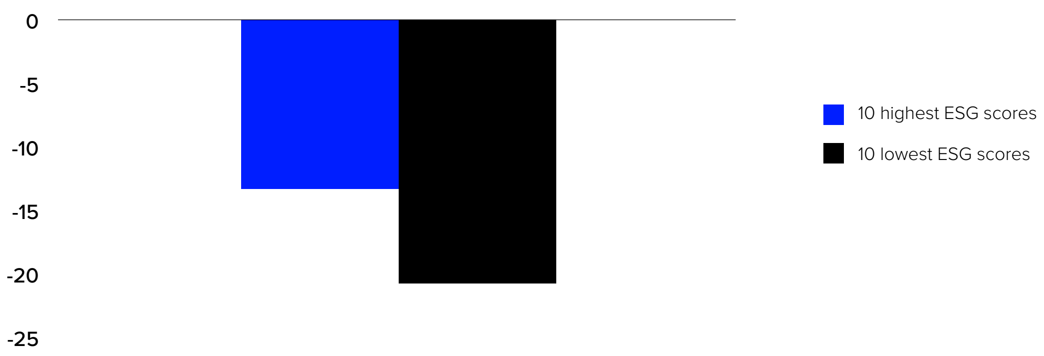
Performance of sustainable firms during COVID-19 epidemics

As we have seen above, highly ESG scoring U.S. firms seem to have lower next year returns than their lower scoring counterparts.

But what does sustainability mean in terms of resilience in the times of crisis? To answer this question, we looked at the losses during COVID-19 pandemic of firms that are in top and bottom 10% of ESG scores. The results are remarkable. In the period from January till May 2020, top 10% ESG scoring firms losses were only 2/3 of the losses encountered by bottom 10% of firms, as illustrated in Figure 4.

Figure 4

Average return till May 13 2020 of companies in S&P 500 with 10 highest and 10 lowest ESG scores



In our subsequent paper, we will address this phenomenon in more detail; for now it is worth mentioning that, for some sectors (such as Utilities, Materials and Health Care), this effect is even more pronounced than for S&P 500 stock universe as a whole.

Concluding remarks

Companies' sustainability measures, i.e., ESG data are becoming increasingly available in many regions, including Asia. Using Refinitiv ESG scores, we examined the relationships between these scores and excess return, market value and volatility, for large cap companies in the U.S., EU, Australia and Asia.

Correlation analysis shows that there is a positive relationship between a company's ESG score and its size. This can be explained by the fact that larger companies have more to invest in sustainability and therefore have higher ESG scores. Investors should be aware of this, as only including highly ESG scoring firms in their portfolio introduces a significant size bias, i.e., skews their portfolios towards larger companies. Furthermore, negative correlations between ESG scores and stock volatility show that higher ESG scoring firms are on average less risky.

The relationship between ESG scores and excess returns of firms was analyzed by means of panel regression models, which, alongside an ESG score, involve several return determinants such as the company's size and its financial ratios. From this analysis, we can conclude that there is positive relationship between ESG scores and excess returns of EU firms. In the same line, highly ESG scoring Australian and South Korean firms do not compromise on returns, as for companies from these two countries the relationship between ESG scores and returns is positive (but not significant). This is arguably the result of the fact that EU and Australia lead institutional investors' embrace of ESG, as witnessed by a recent study of Pensions and Investment (see e.g., https://www.pionline.com/esg/europe-leads-institutional-investors-embrace- esg).

For U.S. and other Asian firms, we observe a significant negative relationship between the ESG scores and excess returns. This seems like a bad news for sustainable investors in U.S. firms. However, zooming in on the resilience of more sustainable U.S. firms during recent COVID-19 crisis, it appears that they were able to weather this storm much better than less sustainable U.S. companies. During that period, losses of companies with low ESG scores were 50% higher than those of highly ESG scoring companies. This effect is particularly pronounced for sectors such as Utilities, Materials and Health Care.

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Appendices

A Additional results

Table 4: Number of stocks for which ESG scores and financial data are available

	U.S.	EU	Australia	Japan	China	South Korea	Asia
2010	433	438	137	352	35	82	469
2011	442	448	151	354	39	88	481
2012	444	455	168	362	41	90	493
2013	452	462	179	367	43	92	502
2014	466	482	196	376	46	97	519
2015	485	500	214	383	46	105	534
2016	488	519	230	391	47	107	545
2017	489	556	242	390	129	109	628
2018	404	546	221	330	130	65	525
Balanced panel	**351**	**414**	**110**	**291**	**31**	**45**	**367**

Table 5: Descriptive statistics of variables, U.S. and EU

	S&P 500				STOXX 600			
	Mean	Var.	Skew.	Kurt.	Mean	Var.	Skew.	Kurt.
ER	0,046	0,096	1,216	9,173	0,079	0,097	1,900	19,789
MV (×100)	0,285	0,189	3,829	20,356	0,242	0,196	5,607	46,441
Var	0,061	0,004	4,614	35,838	0,060	0,003	4,248	30,455
CP	0,111	0,071	28,050	835,436	0,133	0,028	5,110	74,484
BP	0,444	1,504	28,086	844,695	0,630	0,257	2,016	7,593
ESG	0,526	0,039	-0,196	-0,822	0,610	0,037	-0,611	-0,231

Table 6: Descriptive statistics of variables, Australia and Asia

	Australia				Asia			
	Mean	Var.	Skew.	Kurt.	Mean	Var.	Skew.	Kurt.
ER	0,061	0,456	8,569	124,274	0,082	0,125	1,892	11,448
MV (×100)	0,909	4,449	4,201	18,647	0,272	0,261	6,202	51,869
Var	0,155	0,222	14,787	270,056	0,090	0,011	7,622	96,815
CP	0,119	0,023	1,616	28,181	0,156	0,023	-5,151	149,800
BP	0,717	0,278	2,097	13,008	0,920	0,242	1,138	2,046
ESG	0,445	0,046	0,308	-0,829	0,448	0,046	-0,198	-0,980

Table 7: Panel regression model estimates, Japan

	MV	Var	CP	BP	ESG
coeff.	-4,225	**0,823**	0,091	**-0,099**	**-0,420**
sd.	6,912	0,164	0,082	0,045	0,093
t stat.	-0,611	5,032	1,114	-2,201	-4,528
p	0,541	0,000	0,266	0,028	0,000
Haussman stat.			28.070		
pH			0,000		

Significant coefficients at 5% level are in boldface.
The standard deviation, t statistic and p value are calculated by panel-robust estimation.
The Haussman statistic is panel-robust and obtained by 3000 bootstrap samples.

Table 8: Panel regression model estimates, China

	MV	Var	CP	BP	ESG
coeff.	2,581	**0,734**	**1,620**	**0,751**	**-0,604**
sd.	1,742	0,208	0,302	0,141	0,199
t stat.	1,482	3,521	5,359	5,314	-3,033
p	0,140	0,001	0,000	0,000	0,003
Haussman stat.			29.439		
pH			0,000		

Significant coefficients at 5% level are in boldface.
The standard deviation, t statistic and p value are calcu- lated by panel-robust estimation.
The Haussman statistic is panel-robust and obtained by 3000 bootstrap samples.

Table 9: Panel data model estimation results, South Korea

	MV	Var	CP	BP	ESG
coeff.	-0,041	-0,009	0,349	0,060	0,028
sd.	0,721	0,284	0,122	0,053	0,175
t stat.	-0,056	-0,032	2,851	1,146	0,160
p	0,955	0,975	0,005	0,253	0,873
Haussman stat.			9.846		
pH			0.080		

Significant coefficients at 5% level are in boldface.
The standard deviation, t statistic and p value are calculated by panel-robust estimation.
The Haussman statistic is panel-robust and obtained by 3000 bootstrap samples.

Table 10: Descriptive statistics of variables, Japan

	Mean	Var.	Skew.	Kurt.
ER	0,104	0,122	2,030	13,552
MV (×100)	0,344	0,304	5,581	46,920
Var	0,083	0,006	5,758	69,578
CP	0,147	0,020	-8,108	238,249
BP	0,927	0,235	1,136	1,931
ESG	0,440	0,042	-0,231	-0,866

Table 11: Descriptive statistics of variables, China

	Mean	Var.	Skew.	Kurt.
ER	0,000	0,158	1,860	5,348
MV (×100)	3,226	26,196	3,293	12,478
Var	0,131	0,047	5,698	37,915
CP	0,162	0,012	0,473	0,094
BP	0,709	0,102	0,681	-0,159
ESG	0,331	0,026	0,096	-0,759

Table 12: Descriptive statistics of variables, South Korea

	Mean	Var.	Skew.	Kurt.
ER	-0,007	0,100	1,155	2,681
MV (×100)	2,222	24,718	5,943	36,453
Var	0,106	0,013	4,713	35,666
CP	0,214	0,049	-0,743	19,635
BP	1,023	0,349	0,825	1,292
ESG	0,510	0,053	-0,488	-1,056

B Methodology details

When applying panel data model, we should take the individual company effects into consideration. These individual effects capture the time-invariant stock characteristics that are not explicitly specified (or observed).

The relationship between the individual effect with other regressors motivates two different panel data models. If the individual effect is uncorrelated to other regressors, then the individual effect is the so-called *random effect* (RE), otherwise it is called *fixed effect* (FE). To test whether the effect is random or fixed is crucial, because if we treat a fixed effect as random, the model will be misspecified, leading to biased estimates. Here we employ robust version of the well- known Haussman test to examine whether the individual effect is fixed or random. Specifically, we use the so-called *sandwich* variance estimator so that the test is robust against any type of heteroskedasticity or auto-correlation present in the data. This is particularly important in our case, where we have a short panel model (the number of individuals is much larger than the number of time periods). Therefore, we apply a bootstrap procedure to obtain panel-robust version of the Haussman test statistic. The technical details of the panel data model and the corresponding Haussman test can be found below.

B1. Fixed effect and Random effect

The individual effect model specifies as follows:

$$y_{it} = \mu + \alpha_i + \boldsymbol{x}_{it}'\beta + \varepsilon_{it}. \tag{2}$$

with $\boldsymbol{i}$ = 1, . . . , $\boldsymbol{N}$, $\boldsymbol{t}$ = 1, . . . , $\boldsymbol{T}$ and $\boldsymbol{\beta}$ a $[\boldsymbol{K} \times 1]$ vector. Under the assumption that the individual effect is correlated with independent variables, one can equivalently rewrite (2) as

$$\boldsymbol{Q}\boldsymbol{y}_i = \boldsymbol{Q}\boldsymbol{X}_i\beta + \boldsymbol{Q}\boldsymbol{\varepsilon}_i, \quad \boldsymbol{Q} = \boldsymbol{I}_T - T^{-1}\boldsymbol{e}\boldsymbol{e}', \tag{3}$$

as a consequence, one obtains the within estimator:

$$\hat{\beta}_W = (\sum_{i=1}^{N} \boldsymbol{X}_i'\boldsymbol{Q}'\boldsymbol{Q}\boldsymbol{X}_i)^{-1} \sum_{i=1}^{N} \boldsymbol{X}_i'\boldsymbol{Q}'\boldsymbol{Q}\boldsymbol{y}_i$$

with the panel-robust variance estimator

$$V(\hat{\beta}_W) = (\sum_{i=1}^{N}\sum_{t=1}^{T} \tilde{\boldsymbol{x}}_{it}\tilde{\boldsymbol{x}}_{it}')^{-1} \sum_{i=1}^{N}\sum_{t=1}^{T}\sum_{s=1}^{T} \tilde{\boldsymbol{x}}_{it}\tilde{\boldsymbol{x}}_{is}'\hat{\tilde{\varepsilon}}_{it}\hat{\tilde{\varepsilon}}_{is}(\sum_{i=1}^{N}\sum_{t=1}^{T} \tilde{\boldsymbol{x}}_{it}\tilde{\boldsymbol{x}}_{it}')^{-1},$$

where $\tilde{\boldsymbol{x}}_{it} = \boldsymbol{x}_{it} - \bar{\boldsymbol{X}}_i$, and $\hat{\tilde{\varepsilon}}_{it} = \hat{\tilde{\varepsilon}}_{it} - \bar{\hat{\tilde{\varepsilon}}}_i$ is the residual of regression(3).

Now, assuming the individual effect $\boldsymbol{\alpha}_i$ is independent with other explanatory variables $\boldsymbol{x}_{it}$, then equation (2) is equivalent to

$$y_{it} - \lambda\bar{\boldsymbol{y}}_i = (1-\lambda)\mu + (\boldsymbol{x}_{it} - \lambda\bar{\boldsymbol{X}}_i)'\beta + v_{it} \tag{4}$$

with $v_{it} = (1-\lambda)\alpha_i + \varepsilon_{it} - \lambda\bar{\varepsilon}_i$ and $\lambda = 1 - \frac{\sigma_\varepsilon}{\sqrt{T\sigma_\alpha^2 + \sigma_\varepsilon^2}}$ under the assumption $\varepsilon_{it} \sim i.i.d.(0, \sigma_\varepsilon^2)$ and $\alpha_i \sim i.i.d.(0, \sigma_\alpha^2)$. The derivation of equation (4) can be found in Section B3. Obviously, the estimation of σ_ε^2 can be done by the within estimator, that is

$$\hat{\sigma}_\varepsilon^2 = \frac{1}{N(T-1)-K}\sum_{i=1}^{N}\sum_{t=1}^{T}[(y_{it}-\bar{y}_i)-(\boldsymbol{x}_{it}-\bar{\boldsymbol{X}}_i)'\hat{\beta}_w]^2.$$

In order to estimate σ_α^2, we need to employ the Between estimator obtained via the equation

Therefore,

$$\hat{\sigma}_\alpha^2 = \frac{1}{N-(K+1)}\sum_{i=1}^{N}(\bar{y}_i-\hat{\alpha}_B-\bar{\boldsymbol{X}}_i'\hat{\beta}_B)^2-\frac{1}{T}\hat{\sigma}_\varepsilon^2.$$

Finally, the RE estimator is a two-step OLS estimator of regression (4).

B2. Panel-robust Hausman test

The null hypothesis of the Hausman test is

$$\hat{\beta}_{1,RE} = \hat{\beta}_{1,W}.$$

Naturally, the Hausman statistic is defined as following

$$H = (\hat{\beta}_{1,RE}-\hat{\beta}_{1,W})'[\hat{V}(\hat{\beta}_{1,RE})-\hat{V}(\hat{\beta}_{1,W})]^{-1}(\hat{\beta}_{1,RE}-\hat{\beta}_{1,W}).$$

And H follows a $\chi 2(K)$ distribution. However, in practice the individual effect α_i or error term ε_{it} may not be i.i.d.. Under this circumstance, the RE estimator β_{RE} is not fully efficient. Consequently, we calculate panel-robust Hausman statistic with bootstrap. Specifically,

$$H_{robust} = (\hat{\beta}_{1,RE}-\hat{\beta}_{1,W})'[\hat{V}_{boot}(\hat{\beta}_{1,RE}-\hat{\beta}_{1,W})]^{-1}(\hat{\beta}_{1,RE}-\hat{\beta}_{1,W})$$

where

$$\hat{V}_{boot}(\hat{\beta}_{1,RE}-\hat{\beta}_{1,W}) = \frac{1}{B}\sum_{b=1}^{B}(\hat{\delta}_b-\bar{\hat{\delta}})(\hat{\delta}_b-\bar{\hat{\delta}})'$$

and $\hat{\delta} = \hat{\beta}_{1,RE}-\hat{\beta}_{1,W}$.

B3. Proof of the RE estimator

Rewrite equation (2) as below

$$\boldsymbol{y}_i = \boldsymbol{W}_i'\delta + (\boldsymbol{e}\alpha_i + \boldsymbol{\varepsilon}_i), \quad \boldsymbol{W}_i' = [\boldsymbol{e} \quad \boldsymbol{X}_i'] \tag{5}$$

Since $\varepsilon_{it} \sim i.i.d.(0,\sigma_\varepsilon^2)$ and $\alpha_i \sim i.i.d.(0,\sigma_\alpha^2)$, there is

$$\begin{aligned}\Omega &= E[(\boldsymbol{e}\alpha_i)(\boldsymbol{e}\alpha_i)'] = E[\boldsymbol{\varepsilon}_i\boldsymbol{\varepsilon}_i'] + E[\alpha_i^2]\boldsymbol{ee}' \\ &= \sigma_\varepsilon^2\boldsymbol{I}_T + \sigma_\alpha^2\boldsymbol{ee}' \\ &= \sigma_\varepsilon^2[\boldsymbol{Q} + \frac{1}{\phi^2}(\boldsymbol{I}_T-\boldsymbol{Q})]\end{aligned}$$

where $\boldsymbol{Q} = \boldsymbol{I}_T - \frac{1}{T}\boldsymbol{e}\boldsymbol{e}'$ and $\phi^2 = \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + T\sigma_\alpha^2}$. Moreover,

$$
\begin{aligned}
\because \quad & \boldsymbol{Q}\boldsymbol{Q}' = \boldsymbol{Q} \\
\therefore \quad & \Omega^{-1} = \sigma_\varepsilon^{-2}[\boldsymbol{Q} + \phi^2(\boldsymbol{I}_T - \boldsymbol{Q})] \\
& \Omega^{-\frac{1}{2}} = \sigma_\varepsilon^{-1}[\boldsymbol{Q} + \phi(\boldsymbol{I}_T - \boldsymbol{Q})]
\end{aligned}
$$

By multiplying equation (5) by $\Omega^{-\frac{1}{2}}$ on both sides, one obtains

$$
\begin{aligned}
& \Omega^{-\frac{1}{2}}\boldsymbol{y}_i = \Omega^{-\frac{1}{2}}\boldsymbol{W}_i'\delta + \Omega^{-\frac{1}{2}}(\boldsymbol{e}\alpha_i + \boldsymbol{\varepsilon}_i) \\
\therefore \quad & [\boldsymbol{Q} + \phi(\boldsymbol{I}_T - \boldsymbol{Q})]\boldsymbol{y}_i = [\boldsymbol{Q} + \phi(\boldsymbol{I}_T - \boldsymbol{Q})]\boldsymbol{W}_i'\delta + [\boldsymbol{Q} + \phi(\boldsymbol{I}_T - \boldsymbol{Q})](\boldsymbol{e}\alpha_i + \boldsymbol{\varepsilon}_i) \\
\therefore \quad & y_{it} - (1-\phi)\bar{\boldsymbol{y}}_i = (1-(1-\phi))\mu + (\boldsymbol{w}_{it} - (1-\phi)\bar{\boldsymbol{W}}_i)'\beta + \phi\alpha_i + (\varepsilon_{it} - (1-\phi)\bar{\varepsilon}_i)
\end{aligned}
$$

Therefore, equation (4) with $\lambda = 1 - \phi$ is identical to equation (2). More specifically, equation (4) provides the GLS estimators of equation (2).

RE1242765/8-20