ECON-UB 251 Econometrics I

Final Project, Fall 2022 (Ashley Nguyen)

Importance of ESG to individual equity's returns in different geographical regions with noise-correction procedures for ESG ratings

1. Introduction

ESG investing refers to investment strategies that focus on defined sets of environment, social, and corporate governance (ESG) criteria to select their investments that promise higher returns with lower risk. This has gained extreme popularity in the recent decades, as shown in PwC's Asset and Wealth Management Revolution 2022 that ESG-related assets under management (AuM) is expected to increase from USD 18 trillion in 2021 to USD 34 trillion in 2026 (PwC Global). With the substantial inflow of capital into ESG-related assets and multiple studies on the positive effect of ESG on stock returns, this report first substantiated the beneficial impact of ESG using a noise-correction procedure for ESG ratings, then compared this impact in three different regions: America, Europe, and China.

While ESG-related investments and products have been very popular in the finance industry, the academic community has raised several concerns against ESG. The three main arguments why ESG is so controversial that consistently came up in literary research are: (1) Qualitative and subjective ESG ratings from different third-party agencies; (2) Different compliance laws in different parts of the world; (3) Different customer/ investor sentiment in different regions. To address the first concern, this report compared two noise-correction procedures: average and instrumenting to tackle the error-in-variables problem of ESG ratings. The second and third concern will be evaluated through the panel data regression with three random samples from the stock index in three regions mentioned above.

A research paper reviewing 2000 individual studies on the relationship between ESG criteria and corporate financial performance (CFP) shows that roughly 90% of the studies found a nonnegative and stable relationship over time (Busch and Friede). From this literary review, it is expected that this report will also find a nonnegative impact of ESG ratings on company's stock returns. If this correlation is true, the use of noise-correction procedures, specifically using instrument variables, is expected to enhance this effect. Upon comparing the three regions, I would expect ESG criteria to have a stronger positive impact on stock returns in China and Europe where environmental compliance laws are more stringent than America where there are more doubts on this topic.

2. Literature Survey

The research into 3 subtopics in ESG investing gives some background context of which dataset and econometric techniques other researchers used in the past and clarifies how this paper incorporate these findings into applying the best regression model and comparing the impact of ESG criteria in investment screening in China, Europe, and the US.

2.1 ESG stocks have higher returns and lower risk

The most extensive secondary research by Friede studying 2000 papers showed that the majority found a positive correlation between ESG scores and CFP. In 2016, Verheyden implemented a 10% best-in-class approach to incorporating ESG factors into investment decision-making which resulted in a positive contribution to risk-adjusted returns in both global and developed markets (Verheyden et al.). His team compared 3 types of portfolio: unscreened, eliminating 10% worst ESG scorers, and eliminating 25% worst

ESG scorers, and found that ESG screening adds about 0.16% in annual performance, on average. Another research team led by Jacobsen did a point-in-time analysis of the holdings of the MSCI US ESG Leaders Index, the MSCI EAFE ESG Leaders Index, which indicated that portfolios of ESG stocks with positive alpha have similar return-to-risk features to those of non-ESG stocks, but lower residual volatility (Jacobsen et al.).

There is also literature arguing against the case, specifically Schreck 2011 and Nollet 2016. Schreck attempted to address the issue of endogeneity, or a reverse causality between financial performance and corporate social responsibility and found that there is no relationship between profitability and CSR (Schreck). Using the Bloomberg ESG data for S&P 500 firms, Nollet found that there is a negative relationship between ESG and return on capital. However, when imposing a nonlinear relationship, the team observed a U-shaped relationship, potentially indicating positive long-term effects (Nollet et al.).

2.2 Quality of ESG ratings and noise-correction procedures

ESG data is noisy and there are multiple third party ESG rating agencies creating their own indices with different rating criteria. Which ESG ratings should be used for the model? Do they contradict each other? In 2015, Dorfleitner's study suggested that there are significant differences in the way ESG is measured, the scoring approaches, and definitions of corporate social responsibility used by different rating methodologies. Using a large investment universe including S&P 500, Russell 1000, MSCI Europe, FTSE 250, ASX 300, he showed that there is a lack of convergence among all popular ESG rating agencies (Dorfleitner et al.). Another research team from MIT presented an noise-correction procedure using ratings from other ESG rating agencies as instrument variables. Once the noise is corrected for, Berg found that the effect of ESG performance on stock returns is stronger than previously estimated, with the coefficients increasing by an average of 2.6 times. Evaluating against other methods commonly used by practitioners such as averages or principal component analysis, the instrumenting method is more effective (Berg et al.).

2.3 ESG investing in different regions of the world

Most of the research articles focused on one region and offered a more detailed qualitative analysis, while there aren't many papers comparing the effect in different regions. A study by Amundi, a French asset management firm, in 2018 found that a portfolio created using ESG screening outperformed those without this filter. The strategy involved selecting the best-performing stocks based on ESG factors and selling those with poor ESG performance, leading to an additional yield of 3.3% in North America and 6.6% in the Eurozone (Bennani et al.). While there are a very limited number of articles comparing ESG impact on CFP between China and the Western world, the literature focusing on just ESG consequences in China is expanding. Deng and Cheng used data of A-share listed companies and found that there is a positive relationship between ESG indices and its stock market performance. Moreover, the impact of ESG indices is stronger on non-state-owned enterprises than on state-owned enterprises (Deng and Cheng). Confirming that ESG scores also have a positive effect on stock returns in China, we can proceed to look at the model and data.

3. Model

Step 1: Noise correction: Instrument an ESG rating from on agency with another from a different agency. Rate the relevancy by making the correlation map among different agency ESG ratings The model for the first state in TSLS is:

$$RobecoSAM_i = \beta_0 + \beta_1 * ESGScr_i + \epsilon_i$$

Step 2: Regress ESG ratings against the Monthly Return in 3 models using the random sample from the S&P 500. Model (1): Simple OLS

$$MonthlyReturn_i = \beta_0 + \beta_1 * RobecoSAM_i + \epsilon_i$$

Model (2): The second stage of the TSLS

$$MonthlyReturn_i = \beta_0 + \beta_1 * Robec\hat{o}SAM_i + \epsilon_i$$

Model (3): Add other control variables

$$MonthlyReturn_i = \beta_0 + \beta_1 * Robec\hat{o}SAM_i + \beta_2 * Sector + \beta_3 * MarketCap + \beta_4 * PE + \epsilon_i$$

Step 3: Use the best model from the 3 above to compare the ESG ratings impact on monthly returns in 3 different regions.

4. Data

Because of the availability of ESG ratings on Bloomberg, the investment universe include 3 biggest indices: the S&P 500 in America, the STOXX Europe 600 in Europe, and the S&P 500 China in China. There are 17 columns downloaded from Bloomberg Equity Screening function (Ticker, Short Name, Industry Name, Sector, MarketCap, P/E, Alpha, Beta, Monthly Return by 28/11/2022, Government Score, ESG Score, Environmental Score, Social Score, MSCI ESG Rating, RobecoSAM, Sustainalytics). After combining all 3 indices, there are 1678 data points in total.

4.1 Processing Data Code

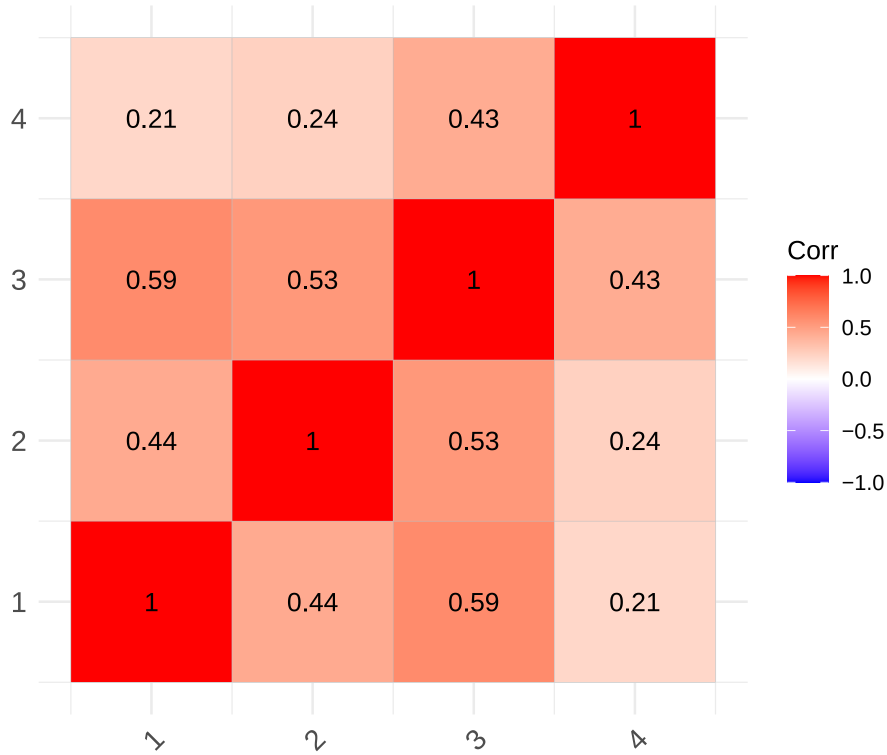
```
# Import data from excel files into R
america <- read_xlsx("/cloud/project/final_proj/america.xlsx", col_names = TRUE)
europe <- read_xlsx("/cloud/project/final_proj/europe.xlsx", col_names = TRUE)
china <- read_xlsx("/cloud/project/final_proj/china.xlsx", col_names = TRUE)

# Add a dummy variable to mark the regions
america <- america %>% mutate(Region = 1)
europe <- europe %>% mutate(Region = 2)
china <- china %>% mutate(Region = 3)

# Combine the 3 data frames by rows
dset <- rbind(america, europe, china)

# Convert MSCI ESG Ratings from letter ratings to numbers
library(dplyr)
dset <- dset %>% mutate(MSCI_ESGRating = recode_factor(MSCI_ESGRating, 'AAA' = '7', 'AA' = '6', 'A' = '5

# Convert all character columns to numeric
column_to_convert <- c("MarketCap", "PE","MonthlyReturn","GovScr", "ESGScr","EnvScr","SocScr","MSCI_ESGR
dset[ , column_to_convert ] <- as.data.frame(apply(dset[ , column_to_convert], 2, as.numeric))

# Convert Sustainalytics score from "Risk from ESG" to proxy score for ESG
dset <- dset %>% mutate(SustainalyticsProxy = 100 - Sustainalytics)
```

5. Empirical Application

5.1 Empirical Results & Discussions

In the first step of TSLS ie. instrument ESG ratings with ratings of other ESG rating agencies, the validity of the instrument variables needs to be checked in order to choose from the 4 third-party ESG ratings in the data set. The two criteria for an instrument variable to be valid are relevance and exogeneity. To pick the most relevant ESG rating out of the 4, a correlation matrix is created. The matrix confirms that the ESG ratings don't converge and the two most suitable to use in our regression model are RobecoSAM and ESGScr by Bloomberg, because they have the highest positive correlation among 4 ESG ratings considered. The reason why these two ESG ratings have high positive correlation could be an overlap of judging criteria. To further test whether our instrument variable is relevant, the F-statistic for the first stage regression is displayed in the coefficient test below. Because the F-statistic for first stage regression is 14.97 which is larger than 10, the instrument is strong and relevant. The second criteria is exogeneity which means that ESG Score by Bloomberg does not affect the error of the second stage regression. Since the coefficient is exactly identified, we can't use J-test, but exogeneity of the instrument is true by the assumption that errors in measuring RobecoSAM are independent of errors in measuring ESG Score by Bloomberg.

```
esg <- cbind(dset$ESGScr,dset$MSCI_ESGRating,dset$RobecoSAM,dset$SustainalyticsProxy)
ggcorrplot(cor(esg, use = "complete.obs"), lab = TRUE)
```




```
stage1 <- lm(RobecoSAM ~ ESGScr, data = dset)
coeftest(stage1, vcov. = vcovHC, type = "HC1")
```

```
t test of coefficients:

            Estimate Std. Error t value Pr(>|t|)
(Intercept)  5.68728    3.90329   1.457   0.1459
ESGScr      12.71011    0.84907  14.970   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

I took a random sample of 300 companies from the S&P 500 and ran 3 models. The first model is just a basic linear regression of monthly returns against the ESG rating RobecoSAM. This shows that there is a positive correlation between RobecoSAM and Monthly Return, but the relationship is not statistically significant. The adjusted R squared is negative, meaning that the model is not a good fit and the ratio of sample size to regressor is low. From model (1), on average, all else being equal, an increase of 1 point in a company's RobecoSAM rating is associated with a predicted increase of 0.003% in monthly return, which is very marginal.

The second model with instrumenting variable shows a higher positive correlation between RobecoSAM and Monthly Return. The interpretation of coefficient in Model (2) is that on average, all else being equal, an increase of 1 point in a company's RobecoSAM rating is associated with a predicted increase of 0.106% in monthly return. This is consistent with the findings in literature survey from Berg. Using instrument variable enhanced the impact of ESG ratings, but it doesn't change the statistical significance of the coefficient. However, one issue with this regression is that there are too many NA values in the random sample and the omission of those NA values can make the result to be positively biased. Rating agencies will be less likely to find out or report the correct ESG scores when the company has not taken much actions to better their ESG aspects. This omission also led to significantly smaller sample size. This might decrease the reliability of the coefficient and the normality of t-stat.

The third model is TSLS with control variables such as sector, market capitalization, and P/E ratio. The impact of ESG rating RobecoSAM goes back to being marginal in this case with only a predicted 0.005% increase in monthly return with an 1-point increase in RobecoSAM score. Again the omission of NA values caused the sample size to be very small here, but the adjusted R squared has increased substantially, which means that model 3 is the best fit model and it can be used to compare among the 3 regions.

```
set.seed(435)
america_random <- dset[sample(nrow(filter(dset, Region == 1)),300),]

m1 <- lm(MonthlyReturn ~ RobecoSAM, data = america_random, na.action=na.omit)
m2 <- ivreg(MonthlyReturn ~ RobecoSAM | ESGScr, data = america_random, na.action=na.omit)
m3 <- ivreg(MonthlyReturn ~ RobecoSAM + Sector + MarketCap + PE | ESGScr + Sector + MarketCap + PE, data
stargazer::stargazer(m1,m2,m3, header=FALSE, type='latex')
```

Compare among 3 regions: .

Repeating the same random sampling process with the 3 regions and applying model 3 to the 3 random samples, we get the table below. As expected, the impact of ESG ratings on monthly returns is the strongest in China and the weakest in America. However, the ESG ratings coefficients are not statistically significant in any of the region.

```
set.seed(305)
america_random <- dset[sample(nrow(filter(dset, Region == 1)),300),]
europe_random <- dset[sample(nrow(filter(dset, Region == 2)),300),]
china_random <- dset[sample(nrow(filter(dset, Region == 3)),300),]

c1 <- ivreg(MonthlyReturn ~ RobecoSAM + Sector + MarketCap + PE | ESGScr + Sector + MarketCap + PE, data
c2 <- ivreg(MonthlyReturn ~ RobecoSAM + Sector + MarketCap + PE | ESGScr + Sector + MarketCap + PE, data
c3 <- ivreg(MonthlyReturn ~ RobecoSAM + Sector + MarketCap + PE | ESGScr + Sector + MarketCap + PE, data

stargazer::stargazer(c1,c2,c3, header=FALSE, type='latex')
```

5.2 Econometric Issues

There are 3 main issues with the data and modelling method in this report.

(1): The original data sets are big indices with only large market capitalization public companies with better than average financial health and higher credibility. This means that most of these companies will be more likely to invest in ESG criteria because they have the financial capacity to and therefore, ESG ratings might be better represented in the large indices.

(2): The validity of instrument is mainly based on the exogenous assumption that the measuring errors of ESG ratings from one agency are independent of those from other agencies. This might need more investigation because while ESG ratings are subjective, the judging criteria among agencies still have overlap. Therefore, measuring errors might not be 100% independent from each other.

(3): The linear regression models in the report are very basic and does not take into account other financial indicators or new events that affect monthly returns.

Table 1:

	Dependent variable:		
	MonthlyReturn		
	OLS	*instrumental variable*	
	(1)	(2)	(3)
RobecoSAM	0.003	0.106	0.005
	(0.021)	(0.124)	(0.065)
SectorConsumer Staples			6.975*
			(3.779)
SectorEnergy			5.751
			(3.914)
SectorInformation Technology			24.623**
			(9.806)
SectorMaterials			10.077**
			(3.826)
SectorReal Estate			6.998*
			(3.962)
SectorUtilities			8.983**
			(3.940)
MarketCap			−0.0001
			(0.008)
PE			0.044
			(0.047)
Constant	3.243**	−2.733	−5.071
	(1.469)	(8.088)	(5.896)
Observations	300	83	81
R^2	0.0001	−0.181	0.330
Adjusted R^2	−0.003	−0.195	0.245
Residual Std. Error	7.954 (df = 298)	6.330 (df = 81)	5.043 (df = 71)
F Statistic	0.017 (df = 1; 298)		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 2:

	Dependent variable:		
	MonthlyReturn		
	(1)	(2)	(3)
RobecoSAM	0.029	0.081	0.180*
	(0.083)	(0.093)	(0.103)
SectorConsumer Staples	6.217	5.936	7.634
	(4.414)	(6.522)	(6.651)
SectorEnergy	7.133	4.570	3.144
	(4.487)	(6.325)	(6.876)
SectorIndustrials		9.188	9.765
		(8.889)	(9.044)
SectorInformation Technology	20.415*	15.254*	23.439**
	(11.205)	(8.591)	(11.647)
SectorMaterials	9.964**	8.202	10.521
	(4.466)	(6.365)	(6.609)
SectorReal Estate	2.523	5.340	5.044
	(4.616)	(6.674)	(6.656)
SectorUtilities	9.651**	8.334	9.163
	(4.461)	(6.241)	(6.808)
MarketCap	0.004	−0.003	−0.003
	(0.009)	(0.005)	(0.005)
PE	0.077	0.028	0.008
	(0.052)	(0.034)	(0.053)
Constant	−7.693	−7.520	−15.563
	(7.353)	(7.945)	(10.803)
Observations	84	111	106
R^2	0.279	0.116	0.093
Adjusted R^2	0.192	0.028	−0.003
Residual Std. Error	5.890 (df = 74)	6.032 (df = 100)	6.379 (df = 95)
Note:			*p<0.1; **p<0.05; ***p<0.01

6. Conclusion

ESG ratings have a positive impact on the return of a company, yet the impact was not statistically significant in the report due to the lack of more control variables or selective sample. Moreover, instrumenting is a good way to eliminate measuring errors among the ESG ratings from different agencies and it also helps to enhance the positive impact of ESG in the regression. Finally, the impact of ESG criteria is most prominent in China potentially due to the strict compliance laws from their authoritarian government, while the impact is positive but weaker in Europe and weakest in America since there are a lot of doubts and fewer environmental compliance laws available.

7. Appendix

7.1 Bibliography

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