Carbon Risk Pricing

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```r
# load packages
library(readxl)
library(tidyverse)
library(AER)
library(dplyr)
library(ggplot2)
library(huxtable)
```

In sustainable finance there are two main hypotesis on how emissions are priced by the stock markets: - Carbon Greening Hypotesis: Higher emissions mean higher dividends that companies offer to attract investors despite being polluters - Future greening hypothesis: Higher emissions mean lower dividends because companies tend to keep money for investing in reducing their environmental impact

The main purpose of this project is therefore to provide an elaboration of a large body of public data by showing some simple and intuitive models for investigating these relationships.

Data load

```r
# load dataset
percorso= "C:/Users/Utente/OneDrive/Desktop/esami fatti/sustainable/sustainable.project/Dataset/dataset2.xlsx"
percorso2 = "C:/Users/Utente/OneDrive/Desktop/esami fatti/sus data/dataset_pollution_col.xlsx"

# financial data for each company
data <- read_excel(percorso,sheet = "Financial Data")

# direct and indirect emissions by company
scope1 <- read_excel(percorso, sheet = "Scope1")
scope2 <- read_excel(percorso, sheet = "Scope2")

# polluter-non polluter label for each company
poll <- read_excel(percorso2, sheet = "Pollution")
```

Data Preprocessing

```
# change the column names
colnames(data) <- c("company", "metric", "2010", "2011", "2012", "2013", "2014", "2015", "2016", "2017", "2018", "2019", "20
20")
colnames(scope1) <- c("company", "country", "economic_sector", "sub_industry", "metric", "2010", "2011", "2012", "2013", "20
14", "2015", "2016", "2017", "2018", "2019", "2020")
colnames(scope2) <- c("company", "metric", "2010", "2011", "2012", "2013", "2014", "2015", "2016", "2017", "2018", "2019",
"2020")

# add to data the label polluter or not polluter for each company
data <- poll %>% left_join(data, by = 'company', multiple = "all")

# find companies with scope1 and scope2 data
datacommon <- intersect(scope1$company, scope2$company)

# find companies with only complete dataset
data_new <- data[data$company %in% datacommon, ]
scope1 <- scope1[scope1$company %in% datacommon, ]

#final dataset with complete informations for each company
df <- scope1[, 1:4] %>% left_join(data_new, by = "company", multiple = "all")

# extract market measures

div <- df[df$metric == "DIVIDEND PAYOUT PER SHARE", ] %>% filter(!is.na(company))
roe <- df[df$metric == "RETURN ON EQUITY - TOTAL (%)", ] %>% filter(!is.na(company))
mrkt <- df[df$metric == "MRKT VALUE TO BOOK", ] %>% filter(!is.na(company))
tot_ass <- df[df$metric == "TOTAL ASSETS", ] %>% filter(!is.na(company))
roa <- df[df$metric == "RETURN ON ASSETS", ] %>% filter(!is.na(company))
cap_ex <- df[df$metric == "CAPITAL EXPENDT % TOTAL ASSETS", ] %>% filter(!is.na(company))


# WEIGHT
tot_ass <- tot_ass %>% mutate(weight_10 = tot_ass[, '2010']/sum(tot_ass[, '2010']))
tot_ass <- tot_ass %>% mutate(weight_11 = tot_ass[, '2011']/sum(tot_ass[, '2011']))
tot_ass <- tot_ass %>% mutate(weight_12 = tot_ass[, '2012']/sum(tot_ass[, '2012']))
tot_ass <- tot_ass %>% mutate(weight_13 = tot_ass[, '2013']/sum(tot_ass[, '2013']))
tot_ass <- tot_ass %>% mutate(weight_14 = tot_ass[, '2014']/sum(tot_ass[, '2014']))
tot_ass <- tot_ass %>% mutate(weight_15 = tot_ass[, '2015']/sum(tot_ass[, '2015']))
tot_ass <- tot_ass %>% mutate(weight_16 = tot_ass[, '2016']/sum(tot_ass[, '2016']))
tot_ass <- tot_ass %>% mutate(weight_17 = tot_ass[, '2017']/sum(tot_ass[, '2017']))
tot_ass <- tot_ass %>% mutate(weight_18 = tot_ass[, '2018']/sum(tot_ass[, '2018']))
tot_ass <- tot_ass %>% mutate(weight_19 = tot_ass[, '2019']/sum(tot_ass[, '2019']))
tot_ass <- tot_ass %>% mutate(weight_20 = tot_ass[, '2020']/sum(tot_ass[, '2020']))

# WEIGHTED Mean dividends
div <- div %>% mutate(wa_10 = div$'2010' * tot_ass$weight_10$'2010')
div <- div %>% mutate(wa_11 = div$'2011' * tot_ass$weight_11$'2011')
div <- div %>% mutate(wa_12 = div$'2012' * tot_ass$weight_12$'2012')
div <- div %>% mutate(wa_13 = div$'2013' * tot_ass$weight_13$'2013')
div <- div %>% mutate(wa_14 = div$'2014' * tot_ass$weight_14$'2014')
div <- div %>% mutate(wa_15 = div$'2015' * tot_ass$weight_15$'2015')
div <- div %>% mutate(wa_16 = div$'2016' * tot_ass$weight_16$'2016')
div <- div %>% mutate(wa_17 = div$'2017' * tot_ass$weight_17$'2017')
div <- div %>% mutate(wa_18 = div$'2018' * tot_ass$weight_18$'2018')
div <- div %>% mutate(wa_19 = div$'2019' * tot_ass$weight_19$'2019')
div <- div %>% mutate(wa_20 = div$'2020' * tot_ass$weight_20$'2020')

div_10 <- div %>% filter(!is.na(wa_10))
div_11 <- div %>% filter(!is.na(wa_11))
div_12 <- div %>% filter(!is.na(wa_12))
div_13 <- div %>% filter(!is.na(wa_13))
div_14 <- div %>% filter(!is.na(wa_14))
div_15 <- div %>% filter(!is.na(wa_15))
div_16 <- div %>% filter(!is.na(wa_16))
div_17 <- div %>% filter(!is.na(wa_17))
div_18 <- div %>% filter(!is.na(wa_18))
div_19 <- div %>% filter(!is.na(wa_19))
div_20 <- div %>% filter(!is.na(wa_20))

div_all <- div[complete.cases(div), ] # 18 observations

year <- c(2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020)
d_w <- c(mean(div_10$wa_10), mean(div_11$wa_11), mean(div_12$wa_12), mean(div_13$wa_13), mean(div_14$wa_14), mean(div_15$wa_
15),
        mean(div_16$wa_16), mean(div_17$wa_17), mean(div_18$wa_18), mean(div_19$wa_19), mean(div_20$wa_20))
new_dw <- data.frame(year, d_w)
new_dw$year <- factor(new_dw$year,levels = new_dw$year)
```

```
# Weight direct emission of each company for the dimension of the company (for each year)
scope1 <- scope1 %>% mutate(wa_10 = scope1$'2010' * tot_ass$weight_10$'2010')
scope1 <- scope1 %>% mutate(wa_11 = scope1$'2011' * tot_ass$weight_11$'2011')
scope1 <- scope1 %>% mutate(wa_12 = scope1$'2012' * tot_ass$weight_12$'2012')
scope1 <- scope1 %>% mutate(wa_13 = scope1$'2013' * tot_ass$weight_13$'2013')
scope1 <- scope1 %>% mutate(wa_14 = scope1$'2014' * tot_ass$weight_14$'2014')
scope1 <- scope1 %>% mutate(wa_15 = scope1$'2015' * tot_ass$weight_15$'2015')
scope1 <- scope1 %>% mutate(wa_16 = scope1$'2016' * tot_ass$weight_16$'2016')
scope1 <- scope1 %>% mutate(wa_17 = scope1$'2017' * tot_ass$weight_17$'2017')
scope1 <- scope1 %>% mutate(wa_18 = scope1$'2018' * tot_ass$weight_18$'2018')
scope1 <- scope1 %>% mutate(wa_19 = scope1$'2019' * tot_ass$weight_19$'2019')
scope1 <- scope1 %>% mutate(wa_20 = scope1$'2020' * tot_ass$weight_20$'2020')

scope1_10 <- scope1 %>% filter(!is.na(wa_10))
scope1_11 <- scope1 %>% filter(!is.na(wa_11))
scope1_12 <- scope1 %>% filter(!is.na(wa_12))
scope1_13 <- scope1 %>% filter(!is.na(wa_13))
scope1_14 <- scope1 %>% filter(!is.na(wa_14))
scope1_15 <- scope1 %>% filter(!is.na(wa_15))
scope1_16 <- scope1 %>% filter(!is.na(wa_16))
scope1_17 <- scope1 %>% filter(!is.na(wa_17))
scope1_18 <- scope1 %>% filter(!is.na(wa_18))
scope1_19 <- scope1 %>% filter(!is.na(wa_19))
scope1_20 <- scope1 %>% filter(!is.na(wa_20))

scope1_all <- scope1[complete.cases(scope1), ] # 18 observations

# weighted emission mean for each year
year <- c(2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020)

sc_w <- c(mean(scope1_10$wa_10), mean(scope1_11$wa_11), mean(scope1_12$wa_12), mean(scope1_13$wa_13), mean(scope1_14$wa_14),
mean(scope1_15$wa_15),
         mean(scope1_16$wa_16), mean(scope1_17$wa_17), mean(scope1_18$wa_18), mean(scope1_19$wa_19), mean(scope1_20$wa_20))

new_scw <- data.frame(year, sc_w)
new_scw$year <- factor(new_scw$year,levels = new_scw$year)


# Weight indirect emission of each company for the dimension of the company (for each year)
scope2 <- scope2 %>% mutate(wa_10 = scope2$'2010' * tot_ass$weight_10$'2010')
scope2 <- scope2 %>% mutate(wa_11 = scope2$'2011' * tot_ass$weight_11$'2011')
scope2 <- scope2 %>% mutate(wa_12 = scope2$'2012' * tot_ass$weight_12$'2012')
scope2 <- scope2 %>% mutate(wa_13 = scope2$'2013' * tot_ass$weight_13$'2013')
scope2 <- scope2 %>% mutate(wa_14 = scope2$'2014' * tot_ass$weight_14$'2014')
scope2 <- scope2 %>% mutate(wa_15 = scope2$'2015' * tot_ass$weight_15$'2015')
scope2 <- scope2 %>% mutate(wa_16 = scope2$'2016' * tot_ass$weight_16$'2016')
scope2 <- scope2 %>% mutate(wa_17 = scope2$'2017' * tot_ass$weight_17$'2017')
scope2 <- scope2 %>% mutate(wa_18 = scope2$'2018' * tot_ass$weight_18$'2018')
scope2 <- scope2 %>% mutate(wa_19 = scope2$'2019' * tot_ass$weight_19$'2019')
scope2 <- scope2 %>% mutate(wa_20 = scope2$'2020' * tot_ass$weight_20$'2020')

scope2_10 <- scope2 %>% filter(!is.na(wa_10))
scope2_11 <- scope2 %>% filter(!is.na(wa_11))
scope2_12 <- scope2 %>% filter(!is.na(wa_12))
scope2_13 <- scope2 %>% filter(!is.na(wa_13))
scope2_14 <- scope2 %>% filter(!is.na(wa_14))
scope2_15 <- scope2 %>% filter(!is.na(wa_15))
scope2_16 <- scope2 %>% filter(!is.na(wa_16))
scope2_17 <- scope2 %>% filter(!is.na(wa_17))
scope2_18 <- scope2 %>% filter(!is.na(wa_18))
scope2_19 <- scope2 %>% filter(!is.na(wa_19))
scope2_20 <- scope2 %>% filter(!is.na(wa_20))

scope2_all <- scope2[complete.cases(scope2), ] # 18 observations

# weighted emission mean for each year
year <- c(2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020)
sc_w2 <- c(mean(scope2_10$wa_10), mean(scope2_11$wa_11), mean(scope2_12$wa_12), mean(scope2_13$wa_13), mean(scope2_14$wa_1
4), mean(scope2_15$wa_15),
         mean(scope2_16$wa_16), mean(scope2_17$wa_17), mean(scope2_18$wa_18), mean(scope2_19$wa_19), mean(scope2_20$wa_20))
new_scw2 <- data.frame(year, sc_w2)
new_scw2$year <- factor(new_scw2$year,levels = new_scw2$year)
```

Then we added the economic size information (considered using total assets) for ongi company

```
# ECONOMIC DIMENSION
tot_ass <- tot_ass %>% mutate(ec_dim_10 = log(tot_ass$'2010'))
tot_ass <- tot_ass %>% mutate(ec_dim_11 = log(tot_ass$'2011'))
tot_ass <- tot_ass %>% mutate(ec_dim_12 = log(tot_ass$'2012'))
tot_ass <- tot_ass %>% mutate(ec_dim_13 = log(tot_ass$'2013'))
tot_ass <- tot_ass %>% mutate(ec_dim_14 = log(tot_ass$'2014'))
tot_ass <- tot_ass %>% mutate(ec_dim_15 = log(tot_ass$'2015'))
tot_ass <- tot_ass %>% mutate(ec_dim_16 = log(tot_ass$'2016'))
tot_ass <- tot_ass %>% mutate(ec_dim_17 = log(tot_ass$'2017'))
tot_ass <- tot_ass %>% mutate(ec_dim_18 = log(tot_ass$'2018'))
tot_ass <- tot_ass %>% mutate(ec_dim_19 = log(tot_ass$'2019'))
tot_ass <- tot_ass %>% mutate(ec_dim_20 = log(tot_ass$'2020'))

tot_ass$quartile <- cut(tot_ass$ec_dim_10, quantile(tot_ass$ec_dim_10),
                        include.lowest = TRUE, labels = c("Small", "Medium", "Large", "Huge"))

#add quartile and pollution info to the measure datatables
div <- tot_ass[, c(1,40)] %>% left_join(div, by = "company")
scope1 <- tot_ass[, c(1,5,40)] %>% left_join(scope1, by = "company")
scope2 <- scope1[, c(1:6)] %>% left_join(scope2, by = 'company')
```

1 The regression Dividend ~ Scope per year

The first model we tried is of the type:

dividend_year ~ 0 + scope_year + quartile + economic sector

This allows us to eliminate the impact of size and economic sector on dividend, for each year (we know these are relevant factors). We can then use the model to see if there is a significant relationship between emissions and dividends for each year, holding other factors constant

```
# prepare data
reg <- cbind(div[, c(1:6,8:18)], scope1[, c(8:18)], scope2[, c(8:18)])

colnames(reg) <- c("company", "quartile", "country", "economic_sector", "sub_industry", "pollution", "d_10", "d_11", "d_12",
"d_13", "d_14", "d_15", "d_16", "d_17", "d_18", "d_19", "d_20",
                   "s1_10", "s1_11", "s1_12", "s1_13", "s1_14", "s1_15", "s1_16", "s1_17", "s1_18", "s1_19", "s1_20",
                  "s2_10", "s2_11", "s2_12", "s2_13", "s2_14", "s2_15", "s2_16", "s2_17", "s2_18", "s2_19", "s2_20")

reg$economic_sector <- as.factor(reg$economic_sector)
reg$quartile <- as.factor(reg$quartile)
```

```
# remove outliers (boxplot were done in another file)
Upper= 4000000
reg_no_out <- subset(reg, reg[,18:29] < Upper)
```

```
#we loose 23 observations checking for outliers
reg_no_out<-reg_no_out[1:40,]
nrow(reg)
```

```
## [1] 63
```

```
nrow(reg_no_out)
```

```
## [1] 40
```

```
# use regr no outliers
reg<-reg_no_out
```

```
#regression dividend scope per year
model_10s1= lm(d_10 ~ 0 + s1_10 + quartile+ economic_sector, data = reg)
model_11s1= lm(d_11 ~ 0 + s1_11 + quartile+ economic_sector, data = reg)
model_12s1= lm(d_12 ~ 0 + s1_12 + quartile+ economic_sector, data = reg)
model_13s1= lm(d_13 ~ 0 + s1_13 + quartile+ economic_sector, data = reg)
model_14s1= lm(d_14 ~ 0 + s1_14 + quartile+ economic_sector, data = reg)
model_15s1= lm(d_15 ~ 0 + s1_15 + quartile+ economic_sector, data = reg)
model_16s1= lm(d_16 ~ 0 + s1_16 + quartile+ economic_sector, data = reg)
model_17s1= lm(d_17 ~ 0 + s1_17 + quartile+ economic_sector, data = reg)
model_18s1= lm(d_18 ~ 0 + s1_18 + quartile+ economic_sector, data = reg)
model_19s1= lm(d_19 ~ 0 + s1_19 + quartile+ economic_sector, data = reg)
model_20s1= lm(d_20 ~ 0 + s1_20 + quartile+ economic_sector, data = reg)
```

Scope1 (direct emissions) has no statistically significant effect on dividends,
now we can try the same method for checking if Scope2 (indirect emissions) have no significant infuence as well.

```r
library(huxtable)
huxreg(
"2010"=model_10s1,
"2011"=model_11s1,
"2012"=model_12s1,
"2013"=model_13s1,
"2014"=model_14s1,
"2015"=model_15s1,
"2016"=model_16s1,
"2017"=model_17s1,
"2018"=model_18s1,
"2019"=model_19s1,
"2020"=model_20s1)
```

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
s1_10	-0.000									
	(0.000)									
quartileSmall	46.420 ***	35.504 **	25.026	41.996 **	66.863 ***	45.489 **	49.929 ***	51.138 ***	51.489 ***	41.418 *
	(8.988)	(11.124)	(12.524)	(13.229)	(14.293)	(14.436)	(9.974)	(12.220)	(10.273)	(17.068)
quartileMedium	42.313 ***	24.176 *	19.228	29.614 *	45.741 **	31.307 *	47.510 ***	62.182 ***	42.749 ***	19.091
	(10.448)	(11.706)	(12.863)	(13.519)	(13.607)	(13.772)	(10.123)	(12.596)	(10.545)	(15.660)
quartileLarge	36.997 **	21.884	13.454	28.153	44.923 **	36.506 *	38.288 **	49.212 **	48.919 ***	23.089
	(11.034)	(13.071)	(14.977)	(17.218)	(16.013)	(15.813)	(12.575)	(17.254)	(12.430)	(18.302)
quartileHuge	51.960 ***	13.968	11.590	34.045	58.516 **	49.850 **	55.739 **	56.280 **	48.904 **	14.643
	(13.320)	(15.707)	(17.158)	(18.045)	(18.619)	(17.891)	(16.705)	(17.872)	(15.595)	(21.907)
economic_sectorEnergy	18.611	-11.781	5.520	-24.244	-42.295	-10.639	-13.940	-5.114	4.596	2.959
	(13.261)	(16.316)	(16.207)	(19.842)	(24.131)	(22.724)	(16.921)	(17.891)	(17.148)	(24.247)
economic_sectorIndustrials	-1.754	15.439	21.227	10.639	-18.632	-1.939	-4.044	-8.229	-2.571	11.197
	(9.370)	(11.046)	(12.718)	(13.612)	(13.424)	(13.564)	(10.165)	(12.790)	(10.543)	(16.214)
economic_sectorTechnology	-0.199	13.082	11.330	6.415	-21.122	-13.806	-20.214	-16.022	-12.298	2.151
	(11.439)	(13.175)	(14.368)	(15.675)	(16.156)	(16.879)	(13.574)	(14.676)	(13.033)	(19.329)
s1_11		0.000								
		(0.000)								
s1_12			0.000							
			(0.000)							
s1_13				0.000						
				(0.000)						
s1_14					-0.000					
					(0.000)					
s1_15						0.000				
						(0.000)				
s1_16							-0.000			
							(0.000)			
s1_17								-0.000		
								(0.000)		
s1_18									-0.000	
									(0.000)	
s1_19										0.000
										(0.000)
s1_20										

N	38	35	33	33	34	34	34	33	34	34
R2	0.864	0.818	0.775	0.788	0.733	0.715	0.800	0.822	0.826	0.684
logLik	-160.538	-151.761	-144.893	-147.751	-156.132	-155.994	-149.644	-147.011	-150.320	-161.682
AIC	339.075	321.522	307.785	313.503	330.264	329.987	317.287	312.021	318.641	341.365

*** p < 0.001; ** p < 0.01; * p < 0.05.

2 The regression dividend~scope2 per year

Scope2 (indirect emissions) have no significant infuence as well.

```
#regression dividend scope per year
model_10s2= lm(d_10 ~ 0 + s2_10 + quartile+ economic_sector, data = reg)
model_11s2= lm(d_11 ~ 0 + s2_11 + quartile+ economic_sector, data = reg)
model_12s2= lm(d_12 ~ 0 + s2_12 + quartile+ economic_sector, data = reg)
model_13s2= lm(d_13 ~ 0 + s2_13 + quartile+ economic_sector, data = reg)
model_14s2= lm(d_14 ~ 0 + s2_14 + quartile+ economic_sector, data = reg)
model_15s2= lm(d_15 ~ 0 + s2_15 + quartile+ economic_sector, data = reg)
model_16s2= lm(d_16 ~ 0 + s2_16 + quartile+ economic_sector, data = reg)
model_17s2= lm(d_17 ~ 0 + s2_17 + quartile+ economic_sector, data = reg)
model_18s2= lm(d_18 ~ 0 + s2_18 + quartile+ economic_sector, data = reg)
model_19s2= lm(d_19 ~ 0 + s2_19 + quartile+ economic_sector, data = reg)
model_20s2= lm(d_20 ~ 0 + s2_20 + quartile+ economic_sector, data = reg)
```

```
# scope2 almost 0 effect but significant in 2015-2016
library(huxtable)
huxreg(
"2010"=model_10s2,
"2011"=model_11s2,
"2012"=model_12s2,
"2013"=model_13s2,
"2014"=model_14s2,
"2015"=model_15s2,
"2016"=model_16s2,
"2017"=model_17s2,
"2018"=model_18s2,
"2019"=model_19s2,
"2020"=model_20s2)
```

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
s2_10	-0.000									
	(0.000)									
quartileSmall	41.859 ***	33.487 **	27.141 *	33.962 *	50.856 ***	41.166 *	46.985 ***	25.420	52.362 ***	36.515 *
	(9.515)	(10.967)	(12.181)	(14.987)	(13.683)	(15.764)	(11.182)	(13.186)	(11.561)	(17.710)
quartileMedium	35.742 **	21.283	21.107	19.516	23.750	26.402	44.013 **	25.950	46.174 **	4.724
	(11.060)	(11.669)	(13.330)	(16.350)	(14.723)	(15.816)	(13.243)	(15.069)	(15.184)	(20.416)
quartileLarge	30.078 *	17.965	15.282	10.525	19.029	31.427	32.981 *	8.967	48.841 ***	19.469
	(12.325)	(13.478)	(15.058)	(23.798)	(16.598)	(17.563)	(13.960)	(16.907)	(13.156)	(18.867)
quartileHuge	43.638 **	10.397	13.819	19.679	34.555	44.259 *	51.392 *	16.573	51.532 *	1.744
	(13.970)	(15.685)	(17.531)	(22.365)	(18.853)	(19.980)	(19.191)	(19.258)	(18.701)	(25.048)
economic_sectorEnergy	9.774	-2.974	12.221	-14.445	-29.962	-4.116	-19.469	7.522	-1.117	18.845
	(13.131)	(15.494)	(15.267)	(17.147)	(22.053)	(19.941)	(14.658)	(16.219)	(16.416)	(21.346)
economic_sectorIndustrials	2.909	18.055	19.327	20.948	-1.455	2.537	-1.304	19.712	-3.930	17.395
	(10.159)	(11.204)	(12.546)	(16.609)	(13.704)	(15.212)	(12.050)	(13.986)	(11.758)	(17.049)
economic_sectorTechnology	5.278	14.258	8.876	11.540	-7.395	-10.392	-17.601	8.505	-13.192	4.118
	(11.529)	(12.693)	(13.800)	(15.966)	(15.198)	(17.662)	(14.598)	(14.602)	(13.836)	(19.359)
s2_11		0.000								
		(0.000)								
s2_12			0.000							
			(0.000)							
s2_13				0.000						

				(0.000)						
s2_14					0.000 *					
					(0.000)					
s2_15						0.000				
						(0.000)				
s2_16							0.000			
							(0.000)			
s2_17								0.000 *		
								(0.000)		
s2_18									-0.000	
									(0.000)	
s2_19										0.000
										(0.000)
s2_20										
N	38	35	33	33	34	34	34	33	34	34
R2	0.856	0.823	0.773	0.796	0.777	0.719	0.797	0.861	0.825	0.689
logLik	-161.650	-151.353	-145.099	-147.060	-153.105	-155.751	-149.903	-142.927	-150.416	-161.394
AIC	341.300	320.707	308.198	312.120	324.210	329.502	317.805	303.853	318.831	340.788

*** p < 0.001; ** p < 0.01; * p < 0.05.

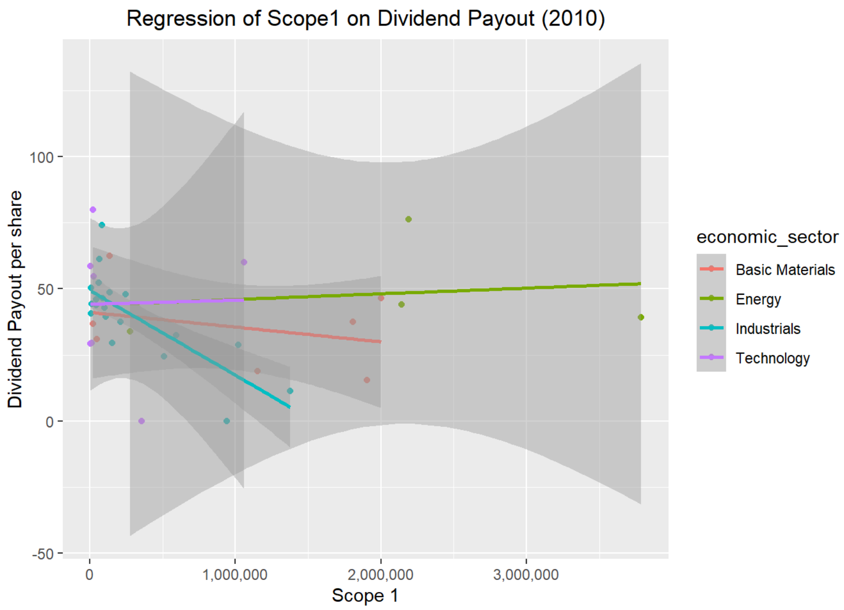
Scope 2 has no significant effect as well

3 Dividend and scope per sector 2010

We can have a look at the regression of scope over dividend divided by secotr, remembering that we have little data and we cannot generalzie from it

```
#dividend e scope 1
library(ggplot2)
ggplot(reg, aes(s1_10, d_10, color = economic_sector)) +
  geom_point() +
  geom_smooth(method = lm) +
  labs(x = "Scope 1", y = "Dividend Payout per share") +
  scale_x_continuous(labels = scales::comma) +
  scale_fill_discrete(name = "Economic Sector") +
  ggtitle("Regression of Scope1 on Dividend Payout (2010)") +
  theme(plot.title = element_text(hjust = 0.5))
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



4 REGRESSION (2010 - 2020): TEST the paris agreements effect

To test whether the paris agreement (2015) had an effect in the emission-dividend relationship we can use a model of the type:

dividend_year ~ 0 + scope + PA + scope*PA + quartile + economic sector

this will allow, given the same size and sector, to test the effect of PAris Agreement (PA) on dividends and its interaction with scope (scope*PA)

```
# reshape for regression
reg2 <- div[, -c(7, 19:28)] %>% gather(year, div, -c(1:6))
reg3 <- scope1[, -c(7)] %>% gather(year, sp1, -c(1:6))
reg4 <- scope2[, -c(7)] %>% gather(year, sp2, -c(1:6))

merge1 <- reg2[, c(1,8)] %>% left_join(reg3, by = 'company', multiple = "all")
```

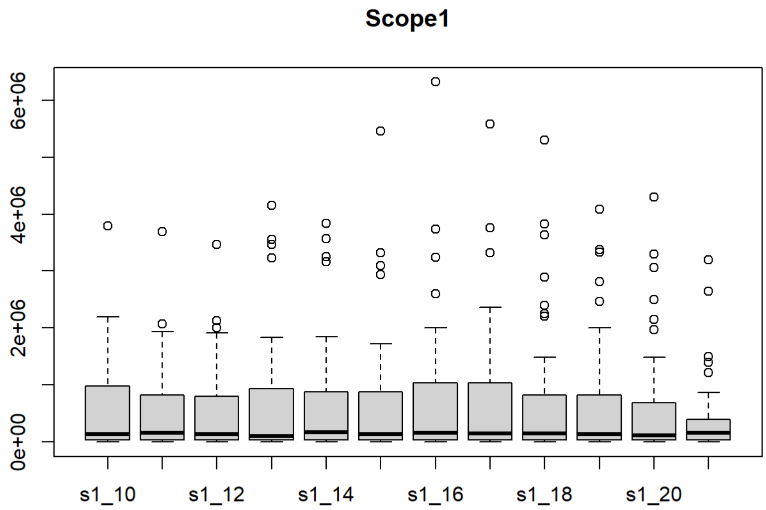
```
## Warning in left_join(., reg3, by = "company", multiple = "all"): Detected an unexpected many-to-many relationship between
`x` and `y`.
## ℹ Row 1 of `x` matches multiple rows in `y`.
## ℹ Row 1 of `y` matches multiple rows in `x`.
## ℹ If a many-to-many relationship is expected, set `relationship =
##   "many-to-many"` to silence this warning.
```

```
merge <- reg4[, c(1,8)] %>% left_join(merge1, by = 'company', multiple = "all")
```

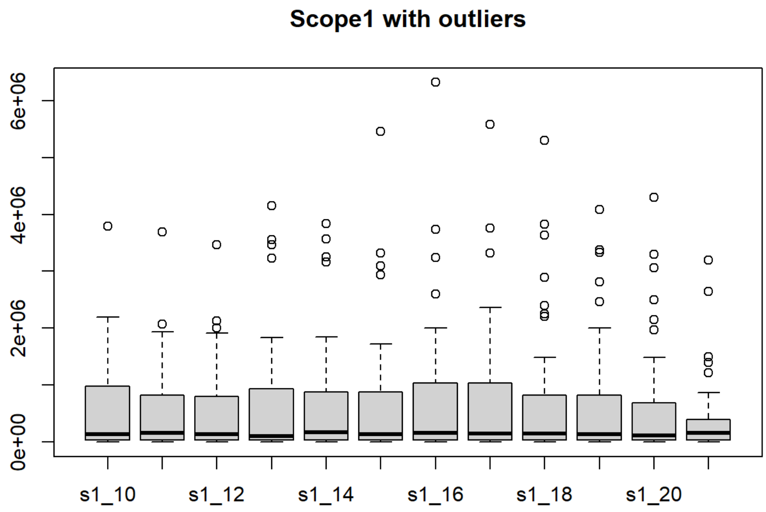
```
## Warning in left_join(., merge1, by = "company", multiple = "all"): Detected an unexpected many-to-many relationship betwe
en `x` and `y`.
## ℹ Row 1 of `x` matches multiple rows in `y`.
## ℹ Row 1 of `y` matches multiple rows in `x`.
## ℹ If a many-to-many relationship is expected, set `relationship =
##   "many-to-many"` to silence this warning.
```

```
merge <- merge[, c(1,6,7,8,4,5,9,3,10,2)]

# add dummy variable paris agreement
merge <- merge %>% mutate(pa = ifelse(year < '2015', 0, 1))

#add dummy variable scope 1 with respect average
merge <- merge %>% mutate(sp1_less_avg = ifelse(sp1 < mean(sp1), 0,1))
```

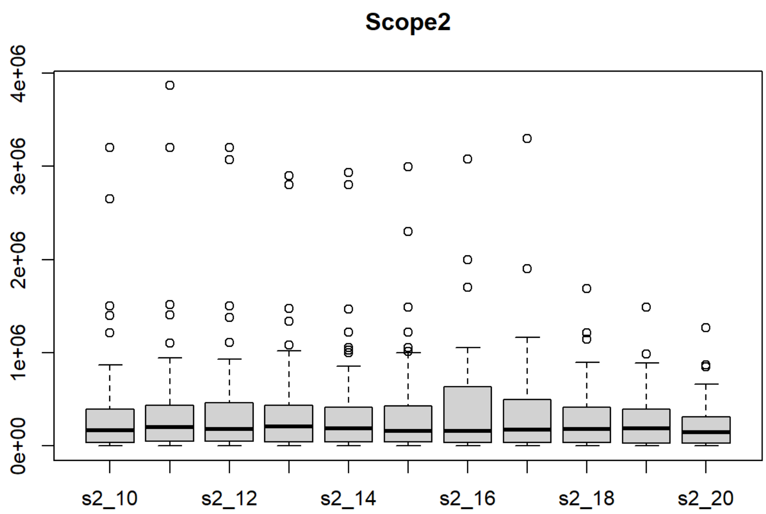
```
# check outliers
Upper= 4000000
reg_no_out <- subset(reg, reg[,18:29] < Upper)
boxplot(reg_no_out[,18:29], main= "Scope1")
```



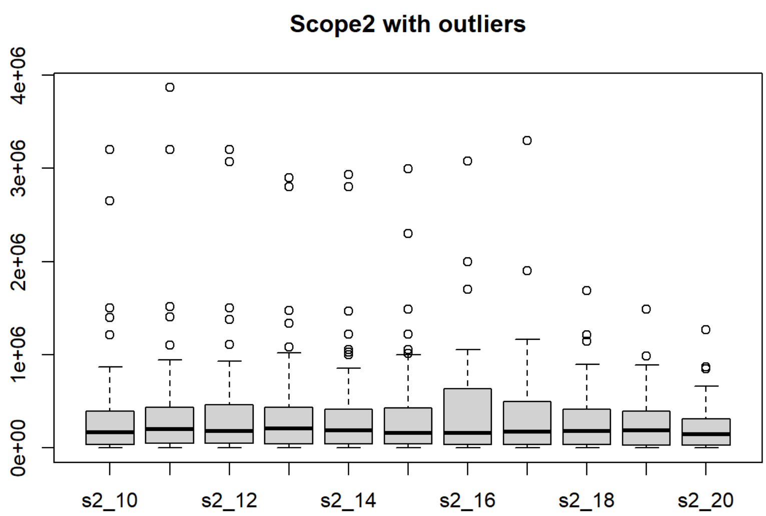

```
boxplot(reg[,18:29], main= "Scope1 with outliers")
```



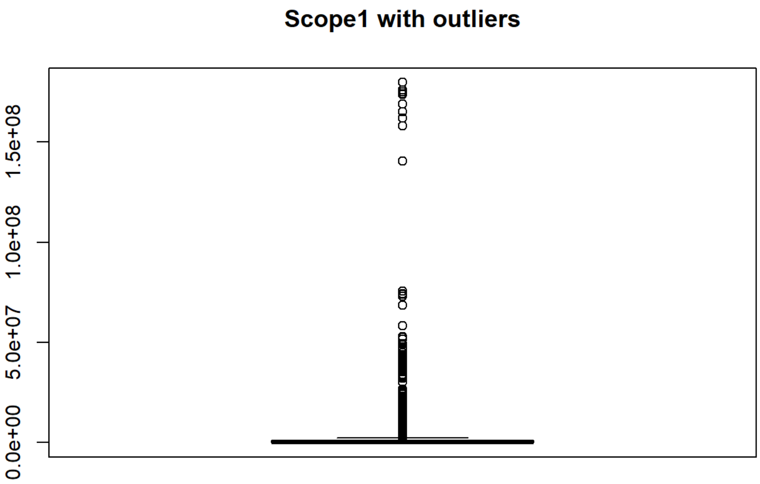

```
boxplot(reg_no_out[,29:39], main= "Scope2")
```



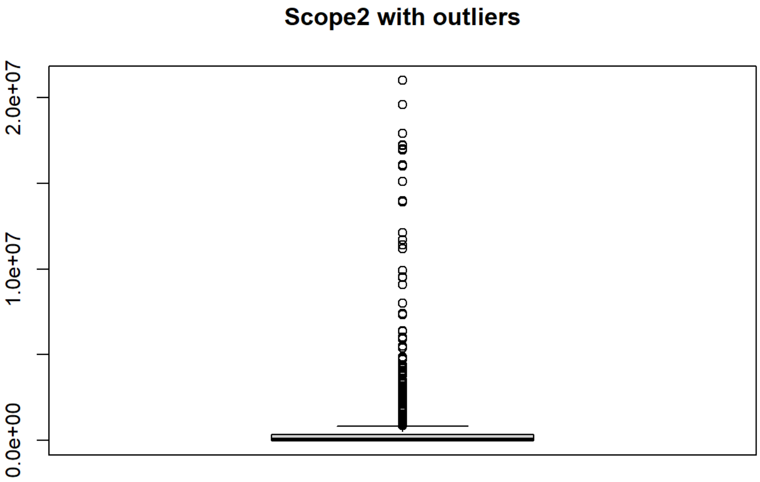

```
boxplot(reg[,29:39], main= "Scope2 with outliers")
```



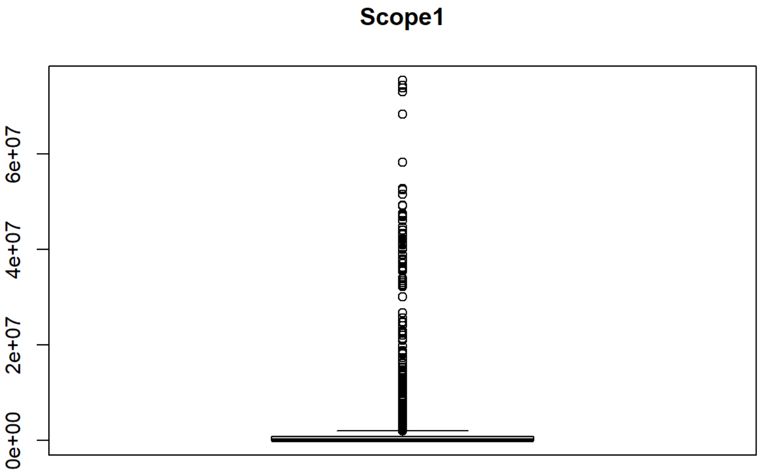

```
boxplot(merge$sp1, main= "Scope1 with outliers")
```



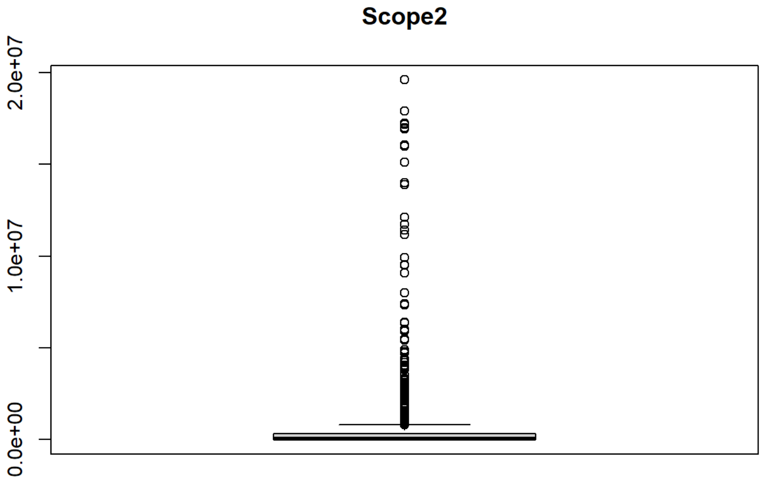

```
boxplot(merge$sp2, main="Scope2 with outliers")
```




```
Upper1 <- 100000000
Upper2<-20000000
reg_no_out <- subset(merge, merge$sp1 < Upper1 &  merge$sp2< Upper2)

boxplot(reg_no_out$sp1, main= "Scope1")
```



```
boxplot(reg_no_out$sp2, main= "Scope2")
```




```
merge_scaled <- merge
scale(merge_scaled[,8:10])
```

```
modello=lm(data= merge, div ~ 0 + sp2+ pa + sp2*pa + economic_sector+ quartile)
huxreg("PA Effect"= modello)
```

	PA Effect
sp2	0.000 ***
	(0.000)
pa	0.000
	(0.114)
economic_sectorBasic Materials	45.758 ***
	(0.160)
economic_sectorEnergy	44.872 ***
	(0.168)
economic_sectorIndustrials	46.013 ***
	(0.136)
economic_sectorTechnology	43.231 ***
	(0.169)
quartileMedium	-12.763 ***
	(0.130)
quartileLarge	-8.542 ***
	(0.135)
quartileHuge	-9.824 ***
	(0.135)
sp2:pa	-0.000
	(0.000)
N	295724
R2	0.698
logLik	-1371259.807
AIC	2742541.613

*** p < 0.001; ** p < 0.01; * p < 0.05.

Conclusions for Scope1:

1. Scope1 seems to have a significant negative effect on dividend (99% s.l.), against the carbon premium hypothesis. But the coefficient is so small that this effect have to be classified as irrelevant and not meaningful.
2. PA coefficient is significant and negative, indicating that on average dividends have decreased after the paris agreement (by little)
3. PA have not influenced the relation dividend-scope1, in fact the Scope*PA effect is not significant*

———————————————————————————————— *(1)*

———————————————— *sp1 -0.000 ***

(0.000)
pa -0.349 **
(0.112)
economic_sectorBasic Materials 49.281 ***
(0.156)
economic_sectorEnergy 47.874 ***
(0.166)
economic_sectorIndustrials 48.859 ***
(0.133)
economic_sectorTechnology 46.854 ***
(0.166)
quartileMedium -12.996 ***
(0.128)
quartileLarge -7.628 ***
(0.132)
quartileHuge -9.130 ***
(0.134)
sp1:pa 0.000
(0.000)

———————————————— N 274912

R2 0.749
logLik -1259651.176
AIC 2519324.352

———————————————————————————————— *** p < 0.001; ** p < 0.01; * p < 0.05.

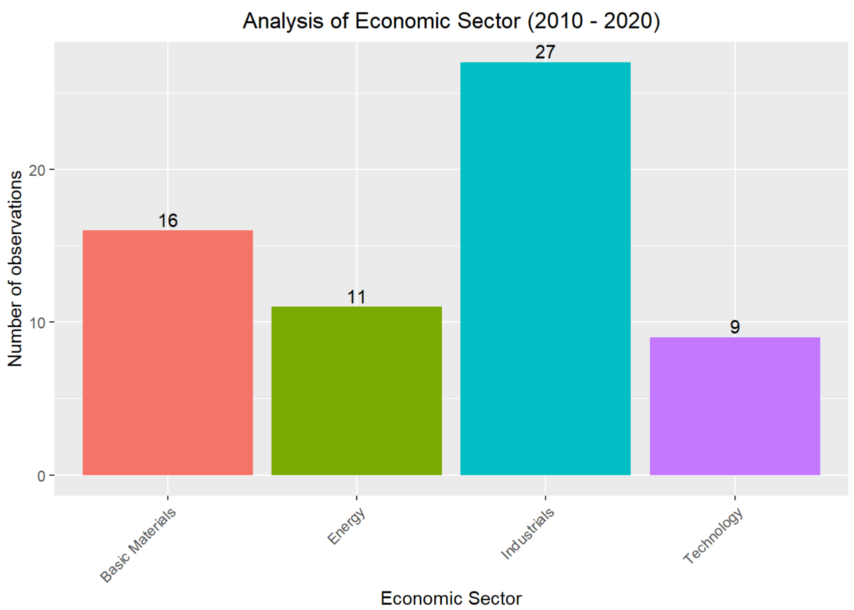
Conclusions for Scope1(same method):

1. Scope2 has a significant positive effect on dividend (99% s.l.),In line the carbon premium hypothesis. But the coefficient is so small (1.416085e-07) hat this effect have to be classified as irrelevant and not meaningful.
2. PA coefficient is not significant
3. PA have not influenced the relation dividend-scope2, in fact the Scope2*PA effect is not significant

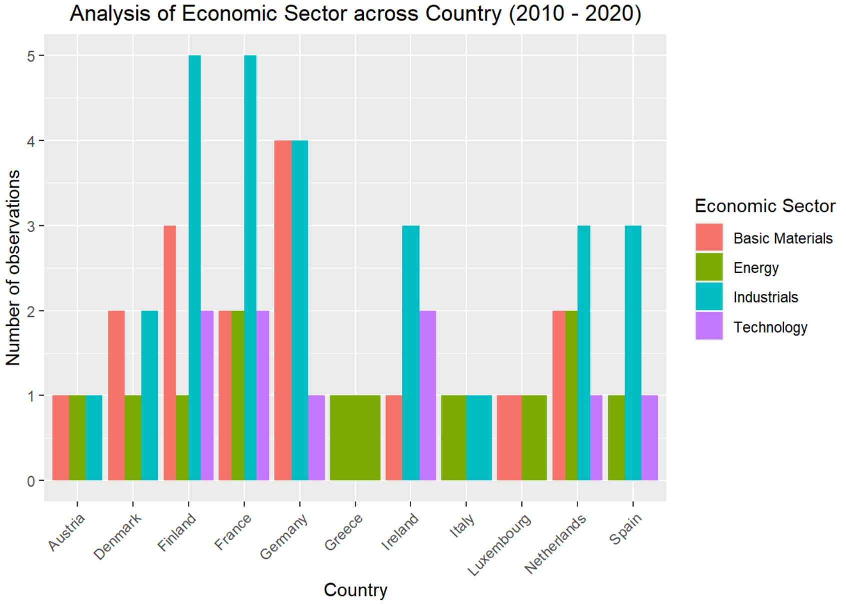
Data exploration that was used

These graphs show our sample (which I recall, is not representative of the true European composition, which is beyond our purposes of representing a methodology for investigating these issues)

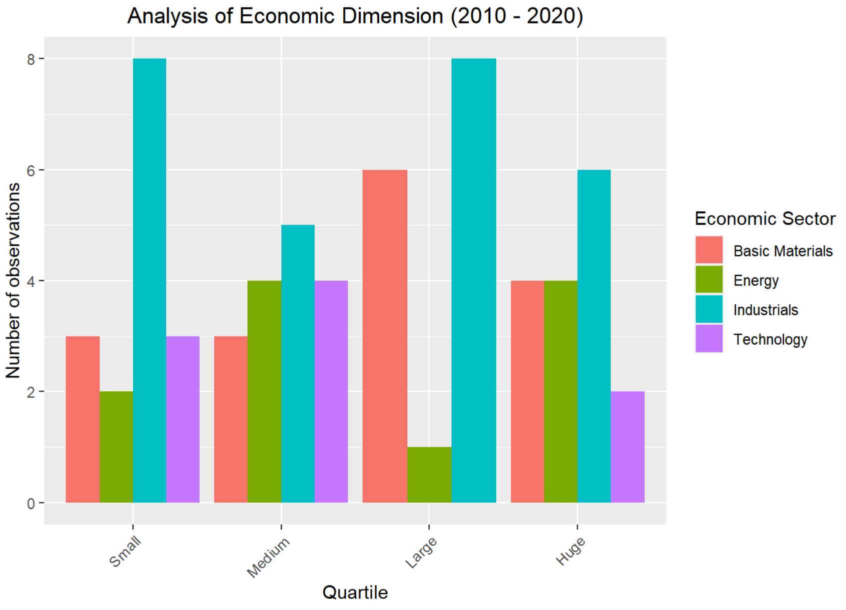
```
# Analysis of Economic Sector
ggplot(scope1, aes(x = economic_sector, fill = economic_sector)) +
  geom_bar(position = position_dodge()) +
  geom_text(stat = 'count', aes(label = after_stat(count)), vjust = -0.30) +
  labs(x = "Economic Sector", y = "Number of observations") +
  ggtitle("Analysis of Economic Sector (2010 - 2020)") +
  guides(fill = 'none') +
  theme(plot.title = element_text(hjust = 0.5), axis.text.x = element_text(angle = 45, vjust = 1, hjust = 1))  #to center
```



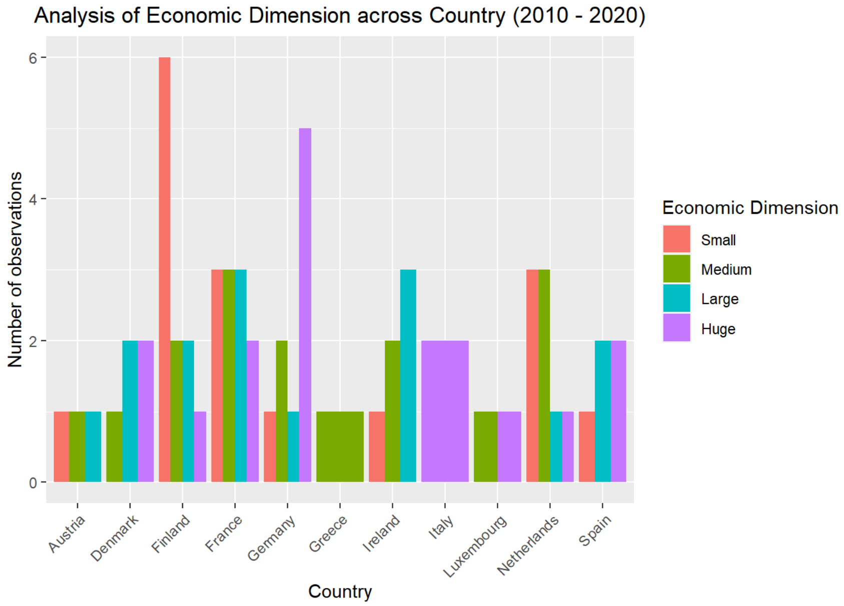
```r
# Analysis of Economic Sector across Country
ggplot(scope1, aes(x = country, fill = economic_sector)) +
  geom_bar(position = position_dodge()) +
  labs(x = "Country", y = "Number of observations") +
  ggtitle("Analysis of Economic Sector across Country (2010 - 2020)") +
  scale_fill_discrete(name = "Economic Sector") +
  theme(plot.title = element_text(hjust = 0.5), axis.text.x = element_text(angle = 45, vjust = 1, hjust = 1))  #to center
```




```r
# Analysis of Economic Dimension across Economic Sector
ggplot(tot_ass, aes(x = quartile, fill = economic_sector)) +
  geom_bar(position = position_dodge()) +
  labs(x = "Quartile", y = "Number of observations") +
  ggtitle("Analysis of Economic Dimension (2010 - 2020)") +
  scale_fill_discrete(name = "Economic Sector") +
  theme(plot.title = element_text(hjust = 0.5), axis.text.x = element_text(angle = 45, vjust = 1, hjust = 1))  #to center
```




```r
# Analysis of Economic Dimension across Country
ggplot(tot_ass, aes(x = country, fill = quartile)) +
  geom_bar(position = position_dodge()) +
  labs(x = "Country", y = "Number of observations") +
  ggtitle("Analysis of Economic Dimension across Country (2010 - 2020)") +
  scale_fill_discrete(name = "Economic Dimension") +
  theme(plot.title = element_text(hjust = 0.5), axis.text.x = element_text(angle = 45, vjust = 1, hjust = 1))  #to center
```




```
# Analysis of Tot Assets across Country
ggplot(tot_ass, aes(x = country, y = '2010', color = economic_sector, size = ec_dim_10)) +
  geom_point(alpha=0.7) +
  labs(x = 'Country', y = 'Total Assets') +
  ggtitle("Analysis of Total Assets (2010)") +
  theme(plot.title = element_text(hjust = 0.5), axis.text.x = element_text(angle = 45, vjust = 1, hjust = 1))  #to center
```