

The Paris Agreement and Financial Markets

Did COP21 generate a differential stock market reaction
between green energy companies and oil & gas companies?

Financial Econometrics and Dataviz

Prof. Fany Declerck

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Yassine Mandengue

Abstract

This study examines whether the Paris Agreement (COP21, December 2015) generated a differential stock market reaction between green energy companies and oil & gas companies. Using a Difference-in-Differences (DiD) framework on daily stock returns of 36 companies across 9 countries over 2013–2018, we find a statistically significant negative DiD coefficient ($\hat{\beta}_3 = -0.120$, $p < 0.01$). Contrary to expectations, green energy stocks underperformed oil & gas stocks in the post-Paris period. This counter-intuitive result may reflect the non-binding nature of the agreement, the oil price recovery in 2016–2017, and the Trump administration’s withdrawal announcement. Fixed effects models and country-level heterogeneity analysis confirm the robustness of our findings.

1 Introduction

The Paris Agreement, adopted on December 12, 2015 at COP21, committed 196 parties to limiting global warming to well below 2°C above pre-industrial levels. If markets efficiently incorporate new information into prices, green energy companies should benefit from this regulatory signal, while oil & gas companies should face negative repricing as their business model becomes increasingly threatened.

This raises a fundamental question: did the Paris Agreement actually affect how markets value polluting versus clean energy companies? If financial markets do not penalize high-carbon firms following major climate policy announcements, it suggests that non-binding international agreements may be insufficient to redirect capital flows toward the energy transition ([Bolton and Kacperczyk, 2021](#)). Understanding these market reactions is critical for designing effective climate finance policies.

2 Motivating Data Visualization

To understand the scale of the challenge, we compare the annual CO₂ emissions of major oil & gas companies in our sample with those of entire nations. We use two publicly available datasets: the Carbon Majors Database (`emissions_low_granularity.csv`) for company-level Scope 1+2+3 emissions in MtCO₂e, and the Global Carbon Budget via Our World in Data (`annual-co2-emissions-per-country.csv`) for national fossil fuel emissions.

The results are striking. Over 2013–2024, ExxonMobil emitted a cumulative 7.89 Gt of CO₂e, Shell 6.13 Gt, and TotalEnergies 4.70 Gt. For comparison, France—a G7 economy—emitted 3.75 Gt, the Netherlands 1.76 Gt, and Belgium 1.14 Gt over the same period. A single oil company thus produces more greenhouse gases than several EU member states combined.

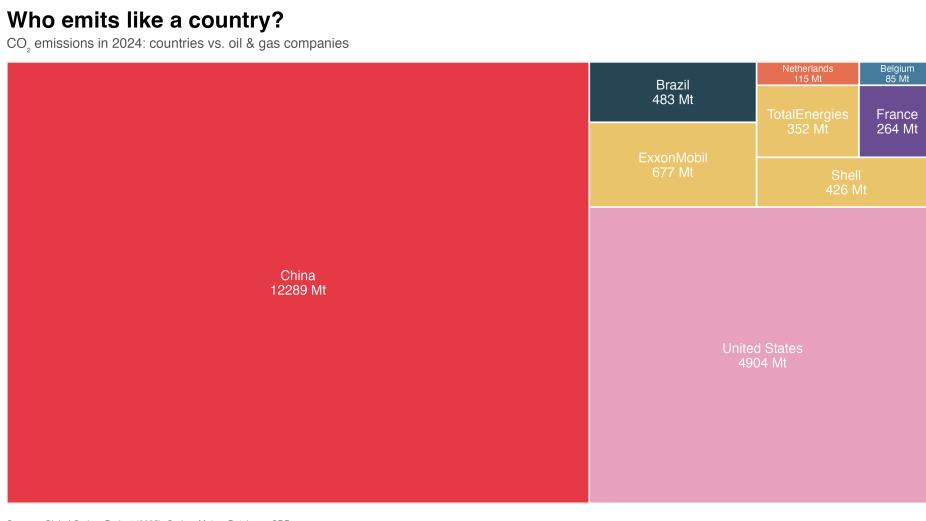


Figure 1: Annual CO₂ emissions (2024): selected countries and oil & gas companies from our sample.

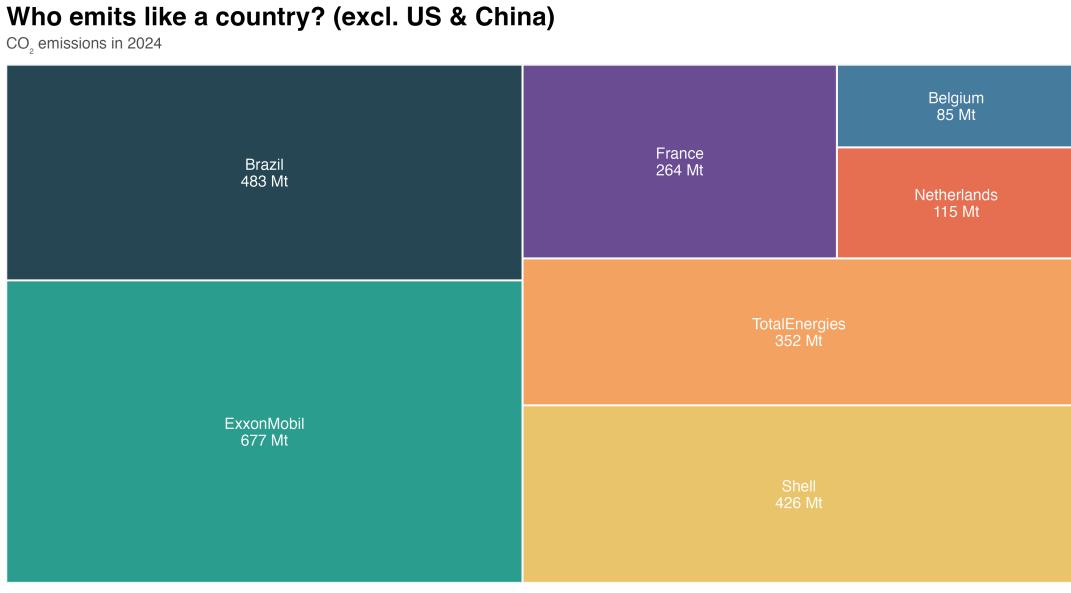


Figure 2: Annual CO₂ emissions (2024): selected countries (Without US and China) and oil & gas companies from our sample.

Figure 2 underscores that the oil & gas companies in our sample are not marginal polluters but systemic contributors to climate change, operating at the same scale as medium-sized nations. Whether financial markets repriced these firms after the Paris Agreement is precisely the question we investigate.

3 Research Question and Hypotheses

Research question: Did the Paris Agreement generate a differential stock market reaction between green energy companies and oil & gas companies?

Null hypothesis (H_0): The Paris Agreement had no differential effect on stock returns between green energy and oil & gas firms ($\beta_3 = 0$).

Alternative hypothesis (H_1): The Paris Agreement generated a significant differential effect on stock returns between the two groups ($\beta_3 \neq 0$).

4 Data Description

We collect daily adjusted closing prices for 36 publicly traded companies across 9 countries over January 2013 to December 2018 from Yahoo Finance. The sample is divided into a *treatment group* (green energy: solar, wind, renewables) and a *control group* (oil & gas producers). Daily returns are computed as percentage changes in adjusted closing prices. The total sample consists of 53,937 firm-day observations.

Table 1: Sample composition by country and sector

Country	Green Energy	Oil & Gas
USA	NextEra Energy, First Solar, Ormat Tech.	ExxonMobil, Chevron
China	LONGi Green, BYD, Xinyi Solar	PetroChina, CNOOC
France	Engie, Veolia	TotalEnergies
UK	SSE, Drax Group	BP, Shell
Germany	Nordex, SMA Solar, Verbio	RWE, E.ON
Japan	Renova, West Holdings	ENEOS, Inpex, Cosmo
Canada	Algonquin, Northland, TransAlta	Suncor, Canadian Natural
Brazil	Engie Brasil, CPFL Energia	Petrobras, PetroRio, Ultrapar
Australia	AGL Energy, Origin Energy	Woodside, Santos

The treatment event is December 12, 2015. The pre-treatment period spans January 2013 to November 2015, and the post-treatment period January 2016 to December 2018. For the motivating visualization (Section 2), company-level emissions come from the Carbon Majors Database and country-level emissions from the Global Carbon Budget ([Friedlingstein et al., 2024](#)).

5 Methodology

We employ a Difference-in-Differences (DiD) framework. Green energy firms constitute the treatment group and oil & gas firms the control group. The baseline specification is:

$$R_{it} = \beta_0 + \beta_1 \text{Treatment}_i + \beta_2 \text{Post}_t + \beta_3 (\text{Treatment}_i \times \text{Post}_t) + \varepsilon_{it} \quad (1)$$

where R_{it} is the daily return of firm i on date t , $\text{Treatment}_i = 1$ for green energy firms, $\text{Post}_t = 1$ after December 2015, and β_3 is the DiD estimator capturing the average treatment effect on the treated (ATT).

We progressively enrich the model: firm fixed effects absorb time-invariant firm characteristics (Model 2), year-month fixed effects control for common time shocks (Model 3), and country-level DiD interactions capture heterogeneous effects (Model 4).

Parallel Trends Assumption

The key identifying assumption of DiD is that, absent the Paris Agreement, both groups would have followed *parallel trends*. While this assumption is fundamentally untestable—it concerns a counterfactual—we can assess its plausibility by examining pre-treatment dynamics.

Figure 3 displays quarterly cumulative returns for green energy and oil & gas firms over a window centered around COP21 (July 2015 to June 2017), normalized to zero at Q4 2015. The grey area marks the pre-treatment period. Prior to COP21, both groups exhibit closely aligned trajectories: they move together from Q3 2015 through Q4 2015, consistent with the parallel

trends assumption.

After the treatment date (dashed line), the series diverge sharply. Oil & gas firms (orange) experience a strong positive rebound, with cumulative returns reaching approximately +0.41 percentage points by Q4 2016, whereas green firms (green) plateau around +0.13 percentage points. This visual divergence corroborates the negative DiD coefficient estimated in our regression models: oil & gas firms outperformed green firms in the post-Paris period.

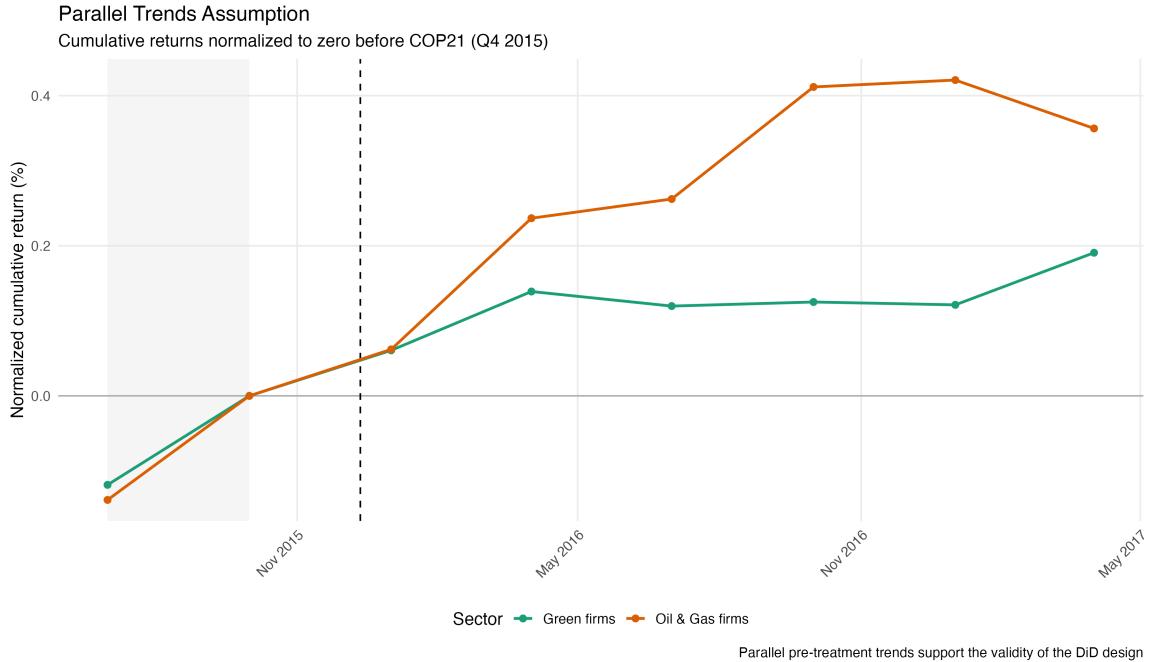


Figure 3: Parallel trends test. Quarterly cumulative returns normalized to zero at Q4 2015 (just before COP21).

6 Results

Table 2 presents the DiD estimation results across four specifications.

Dependent Variable:	Return			
Model:	(1)	(2)	(3)	(4)
<i>Variables</i>				
Constant	-0.024 (0.018)			
Green firm	0.085*** (0.025)			
Post-COP21	0.085*** (0.025)	0.085*** (0.025)		
Treatment \times Post	-0.120*** (0.034)	-0.121*** (0.034)	-0.087** (0.034)	-0.431*** (0.076)
Treatment \times Post \times Country Australie				0.457*** (0.101)
Treatment \times Post \times Country Bresil				0.449*** (0.102)
Treatment \times Post \times Country Canada				0.501*** (0.102)
Treatment \times Post \times Country Chine				0.250** (0.105)
Treatment \times Post \times Country France				0.307*** (0.101)
Treatment \times Post \times Country Japon				0.323*** (0.102)
Treatment \times Post \times Country UK				0.456*** (0.101)
Treatment \times Post \times Country USA				0.343*** (0.093)
<i>Fixed-effects</i>				
Ticker		Yes	Yes	Yes
YearMonth			Yes	Yes
<i>Fit statistics</i>				
Observations	53,937	53,937	53,937	53,937
R ²	0.00029	0.00051	0.00875	0.00943

IID standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 2: Difference-in-Differences estimation results. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Across all specifications, the DiD coefficient is negative and statistically significant. In Model 1,

$\hat{\beta}_3 = -0.120$ ($p < 0.01$), indicating that green energy stocks experienced daily returns approximately 0.12 percentage points lower than oil & gas stocks in the post-Paris period, relative to the pre-treatment differential. This result is robust to firm fixed effects (Model 2: -0.121) and remains significant with firm and time fixed effects (Model 3: -0.087 , $p < 0.05$).

Model 4 reveals substantial country-level heterogeneity. The base DiD effect is -0.431 (highly significant), with positive interaction terms partially offsetting this effect. Canada (+0.501), Australia (+0.457), UK (+0.456), and Brazil (+0.449) show the largest offsets, resulting in near-zero net effects. China (+0.250) exhibits the smallest offset, suggesting that Chinese financial markets displayed the strongest negative differential between green and fossil fuel stocks after the Paris Agreement.

6.1 Discussion

The finding that green stocks underperformed oil & gas stocks post-COP21 is counter-intuitive but can be explained by several concurrent factors:

1. **Non-binding agreement.** The Paris Agreement imposes no immediate penalties on polluters, limiting market incentive for repricing (Dietz et al., 2016).
2. **Oil price recovery.** The 2016–2017 oil price rebound—following the 2014–2015 crash—benefited fossil fuel companies whose valuations had been severely depressed.
3. **Political reversal.** The election of Donald Trump (November 2016) and the subsequent US withdrawal announcement (June 2017) created significant uncertainty for the clean energy sector.
4. **“Buy the rumor, sell the news.”** Investors may have priced in the Agreement before its official adoption, leading to a correction afterward.

These findings suggest that non-binding international climate agreements, while symbolically important, may be insufficient to redirect financial flows from fossil fuels to clean energy through market mechanisms alone.

7 Bibliography

References

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- Dietz, S., Bowen, A., Dixon, C., and Gradwell, P. (2016). Climate value at risk of global financial assets. *Nature Climate Change*, 6(7), 676–679.
- Friedlingstein, P., Jones, M. W., O’Sullivan, M., et al. (2024). Global Carbon Budget 2024. *Earth System Science Data*, 16, 4655–4740.
- Heede, R. (2014). Tracing anthropogenic carbon dioxide and methane emissions to fossil fuel and cement producers, 1854–2010. *Climatic Change*, 122(1), 229–241.
- Kleiber, C. and Zeileis, A. (2008). *Applied Econometrics with R*. Springer.

Data Sources

- **Stock prices:** Yahoo Finance via `yfinance` Python library
- **Company CO₂ emissions:** Carbon Majors Database — `emissions_low_granularity.csv` (<https://carbonmajors.org>)
- **Country CO₂ emissions:** Global Carbon Budget — `annual-co2-emissions-per-country.csv` (<https://ourworldindata.org/co2-emissions>)

Annex: Code

```
1 #####  
2 # FINANCIAL ECONOMETRICS PROJECT  
3 # Author : Yassine Mandengue  
4 #####  
5  
6 #####  
7 # PACKAGES  
8 #####  
9 #####  
10  
11 library(tidyverse)  
12 library(scales)  
13 library(ggtext)  
14 library(lubridate)  
15 library(fixest)  
16 library(treemapify)  
17  
18 #####  
19 # PART I      MOTIVATIONAL DATA VISUALIZATION  
20 # "Who emits like a country?"  
21 #####  
22 # -----  
23 # 1. Data Import  
24 # -----  
25 emissions_low_granularity <- read_csv("Downloads/emissions_low_granularity.csv")  
26  
27 annual_co2_emissions_per_country <- read_csv(  
28   "Desktop/M2_FIRE/Classes/Financial_Econometrics_and_dataviz/Project/  
29   annual-co2-emissions-per-country.filtered/  
30   annual-co2-emissions-per-country.csv"  
31 )  
32  
33 # -----  
34 # 2. Country-Level Data Preparation  
35 # -----  
36 # - Select a subset of representative countries  
37 # - Restrict the period to 2013-2024  
38 # - Convert emissions from tonnes to million tonnes (MtCO2)  
39  
40 df_countries <- annual_co2_emissions_per_country %>%  
41 filter(  
42   Entity %in% c("United_States", "China", "Brazil",  
43   "France", "Netherlands", "Belgium"),  
44   Year >= 2013, Year <= 2024  
45 ) %>%  
46 transmute(
```

```

51     Year = Year,
52     Entity = Entity,
53     Emissions_Mt = round('Annual CO2 emissions' / 1e6, 2)
54   )
55
56
57 # -----
58 # 3. Company-Level Data Preparation
59 # -----
60 # - Focus on major oil & gas companies
61 # - Emissions already expressed in MtCO2e
62 # - Include Scope 1, 2 and 3 emissions
63
64 df_companies <- emissions_low_granularity %>%
65   filter(
66     parent_entity %in% c("ExxonMobil", "Shell", "TotalEnergies"),
67     year >= 2013, year <= 2024
68   ) %>%
69   transmute(
70     Year = year,
71     Entity = parent_entity,
72     Emissions_Mt = round(total_emissions_MtCO2e, 2)
73   )
74
75
76 # -----
77 # 4. Merge Countries and Companies
78 # -----
79 # - Create a unified long-format dataset
80 # - Define entity type
81 # - Set factor order for stacked visualization
82
83 data_long <- bind_rows(df_countries, df_companies) %>%
84   mutate(
85     Type = case_when(
86       Entity %in% c("United States", "China", "Brazil",
87                     "France", "Netherlands", "Belgium") ~ "Country",
88       TRUE ~ "Company"
89     ),
90     Entity = factor(
91       Entity,
92       levels = c(
93         "China", "United States",
94         "ExxonMobil", "Shell", "TotalEnergies",
95         "Brazil", "France",
96         "Netherlands", "Belgium"
97       )
98     )
99   )
100
101
102 # -----

```

```

103 # Treemap 5      DataViz F4A261
104 # -----
105 # Last year
106 latest_year <- max(data_long$Year)
107
108 treemap_data <- data_long %>%
109   filter(Year == latest_year)
110
111 # --- Colors ---
112 colors_entities <- c(
113   "China"          = "#E63946",
114   "United States" = "#E8A0BF",
115   "ExxonMobil"     = "#2A9D8F",
116   "Shell"          = "#E9C46A",
117   "TotalEnergies"  = "#F4A261",
118   "Brazil"         = "#264653",
119   "France"         = "#6A4C93",
120   "Netherlands"   = "#E76F51",
121   "Belgium"        = "#457B9D"
122 )
123
124 colors_entities2 <- c(
125   "China"          = "#E63946",
126   "United States" = "#E8A0BF",
127   "ExxonMobil"     = "#E9C46A",
128   "Shell"          = "#E9C46A",
129   "TotalEnergies"  = "#E9C46A",
130   "Brazil"         = "#264653",
131   "France"         = "#6A4C93",
132   "Netherlands"   = "#E76F51",
133   "Belgium"        = "#457B9D"
134 )
135
136 p_tree_all <- ggplot(treemap_data, aes(
137   area = Emissions_Mt,
138   fill = Entity,
139   label = paste0(Entity, "\n", round(Emissions_Mt), " Mt"))
140 ) +
141   geom_treemap(color = "white", size = 2) +
142   geom_treemap_text(
143     colour = "white",
144     place = "centre",
145     size = 12,
146     grow = FALSE,
147     reflow = TRUE
148 ) +
149   scale_fill_manual(values = colors_entities2) +
150   labs(
151     title = "Who emits like a country?",
152     subtitle = paste0(" CO emissions in ", latest_year, " countries vs oil &
153       gas companies"),

```

```

153     caption = "Sources: Global Carbon Budget (2025), Carbon Majors Database, CDP
154     \nNote: Company emissions include Scope 1, 2, and 3"
155 ) +
156 theme_minimal(base_size = 13) +
157 theme(
158   plot.title      = element_text(face = "bold", size = 20, margin = margin(b =
159     5)),
160   plot.subtitle = element_text(size = 12, color = "gray30", margin = margin(b =
161     10)),
162   plot.caption   = element_text(size = 8, color = "gray50", hjust = 0, margin =
163     margin(t = 15)),
164   legend.position = "none",
165   plot.margin = margin(20, 20, 15, 15)
166 )
167
168 p_tree_all
169
170 # -----
171 # Treemap 5.1      Without US and China
172 # -----
173
174 treemap_data_excl <- treemap_data %>%
175   filter(!Entity %in% c("United States", "China"))
176
177 p_tree_excl <- ggplot(treemap_data_excl, aes(
178   area = Emissions_Mt,
179   fill = Entity,
180   label = paste0(Entity, "\n", round(Emissions_Mt), " Mt"))
181 )) +
182   geom_treemap(color = "white", size = 2) +
183   geom_treemap_text(
184     colour = "white",
185     place = "centre",
186     size = 12,
187     grow = FALSE,
188     reflow = TRUE
189   ) +
190   scale_fill_manual(values = colors_entities) +
191   labs(
192     title = "Who emits like a country? (excl.US & China)",
193     subtitle = paste0(" CO emissions in ", latest_year),
194     caption = "Sources: Global Carbon Budget (2025), Carbon Majors Database, CDP
195     "
196   )
197 theme_minimal(base_size = 13) +
198 theme(
199   plot.title      = element_text(face = "bold", size = 20, margin = margin(b =
200     5)),
201   plot.subtitle = element_text(size = 12, color = "gray30", margin = margin(b =
202     10)),
203   plot.caption   = element_text(size = 8, color = "gray50", hjust = 0, margin =
204     margin(t = 15)),

```

```

197     legend.position = "none",
198     plot.margin = margin(20, 20, 15, 15)
199   )
200
201 p_tree_excl
202
203 #####
204 # PART II      STOCK RETURNS AND PARALLEL TRENDS
205 #####
206 #####
207
208 # -----
209 # 1. Stock Prices and Metadata
210 #
211
212 prices <- read_csv("stock_prices.csv") %>%
213   mutate(Date = as.Date(Date))
214
215 metadata <- read_csv("companies_metadata.csv") %>%
216   mutate(Treatment = ifelse(Sector == "Green", 1, 0))
217
218
219 # -----
220 # 2. Long Format and Cleaning
221 #
222
223 prices_long <- prices %>%
224   pivot_longer(cols = -Date, names_to = "Ticker", values_to = "Price") %>%
225   filter(!is.na(Price)) %>%
226   arrange(Ticker, Date) %>%
227   left_join(metadata, by = "Ticker") %>%
228   filter(!is.na(Sector))
229
230
231 # -----
232 # 3. Return Computation
233 #
234 # Returns are computed over the full sample to ensure precision.
235
236 returns_data <- prices_long %>%
237   group_by(Ticker) %>%
238   arrange(Date) %>%
239   mutate(
240     Return = (Price / lag(Price) - 1) * 100,
241     Log_Return = log(Price / lag(Price)) * 100
242   ) %>%
243   ungroup() %>%
244   filter(!is.na(Return))
245
246
247 # -----
248 # 4. Event Window Around COP21

```

```

249 # -----
250
251 returns_data_filtered <- returns_data %>%
252   filter(Date >= "2015-07-01" & Date <= "2017-06-30")
253
254 cop21_date <- as.Date("2015-12-12")
255
256
257 # -----
258 # 5. Parallel Trends Quarterly Aggregation
259 # -----
260
261 quarterly_returns <- returns_data_filtered %>%
262   mutate(Quarter = floor_date(Date, "quarter")) %>%
263   group_by(Quarter, Sector) %>%
264   summarise(Mean_Return = mean(Return, na.rm = TRUE), .groups = "drop")
265
266 quarterly_cumulative <- quarterly_returns %>%
267   arrange(Sector, Quarter) %>%
268   group_by(Sector) %>%
269   mutate(Cumulative_Return = cumsum(Mean_Return)) %>%
270   ungroup()
271
272 # Normalization at Q4 2015 (just before COP21)
273 baseline_quarter <- as.Date("2015-10-01")
274
275 baseline_values <- quarterly_cumulative %>%
276   filter(Quarter == baseline_quarter) %>%
277   select(Sector, Baseline = Cumulative_Return)
278
279 quarterly_normalized <- quarterly_cumulative %>%
280   left_join(baseline_values, by = "Sector") %>%
281   mutate(Normalized_Return = Cumulative_Return - Baseline)
282
283
284 # -----
285 # 6. Parallel Trends Visualization
286 # -----
287
288 plot_parallel_trends <- ggplot(
289   quarterly_normalized,
290   aes(x = Quarter, y = Normalized_Return, color = Sector)
291 ) +
292   annotate("rect",
293     xmin = min(quarterly_normalized$Quarter),
294     xmax = baseline_quarter,
295     ymin = -Inf, ymax = Inf,
296     fill = "grey90", alpha = 0.4) +
297   geom_hline(yintercept = 0, color = "grey60", linewidth = 0.4) +
298   geom_vline(xintercept = cop21_date, linetype = "dashed") +
299   geom_line(linewidth = 1) +
300   geom_point(size = 2) +

```

```

301 |     scale_color_manual(
302 |       values = c("Green" = "#1B9E77", "Oil_Gas" = "#D95F02"),
303 |       labels = c("Green" = "Green_firms", "Oil_Gas" = "Oil&Gas_firms"))
304 |   ) +
305 |     scale_x_date(date_breaks = "6_months", date_labels = "%b%Y") +
306 |   labs(
307 |     title = "Parallel Trends Assumption",
308 |     subtitle = "Cumulative returns normalized to zero before COP21 (Q4 2015)",
309 |     y = "Normalized cumulative return (%)",
310 |     x = NULL,
311 |     caption = "Parallel pre-treatment trends support the validity of the DiD design"
312 |   ) +
313 |   theme_minimal(base_size = 13) +
314 |   theme(
315 |     legend.position = "bottom",
316 |     panel.grid.minor = element_blank(),
317 |     axis.text.x = element_text(angle = 45, hjust = 1)
318 |   )
319 |
320 | plot_parallel_trends
321
322 #####
323 # PART III DIFFERENCE-IN-DIFFERENCES ESTIMATION
324 #####
325 #####
326
327 did_data <- returns_data %>%
328   mutate(
329     Post = ifelse(Date >= cop21_date, 1, 0),
330     DiD = Post * Treatment,
331     YearMonth = floor_date(Date, "month")
332   )
333
334 #
335 # -----
336 # DiD Models
337 # -----
338
339 # Model 1: Simple DiD (OLS)
340 model1 <- feols(Return ~ Treatment + Post + DiD, data = did_data)
341 summary(model1)
342
343 # Model 2: DiD with firm fixed effects
344 model2 <- feols(Return ~ Post + DiD | Ticker, data = did_data)
345 summary(model2)
346
347 # Model 3: DiD with firm and time fixed effects
348 model3 <- feols(Return ~ DiD | Ticker + YearMonth, data = did_data)
349 summary(model3)
350
351 # Model 4: Heterogeneous effects by country

```

```

352 model4 <- feols(Return ~ DiD * Country | Ticker + YearMonth, data = did_data)
353 summary(model4)
354
355
356
357 # =====
358 # EXPORT PLOTS
359 # =====
360
361 ggsave("ptree_all.png", p_tree_all, width = 12, height = 7, dpi = 300)
362 ggsave("ptree.png", p_tree_excl, width = 12, height = 7, dpi = 300)
363 ggsave("parallel_trend.png", plot_parallel_trends, width = 12, height = 7, dpi =
300)
364
365
366
367 # =====
368 # EXPORT DiD RESULTS TO LATEX TABLE
369 # =====
370
371 etable(
372   model1, model2, model3, model4,
373   tex = TRUE,
374   file = "did_results.tex",
375   title = "Difference-in-Differences\u2022Estimation\u2022Results",
376   dict = c(
377     Treatment = "Green\u2022firm",
378     Post = "Post-COP21",
379     DiD = "Treatment\u00d7\u00d7Post"
380   ),
381   se.below = TRUE,
382   digits = 3,
383   fitstat = ~ n + r2,
384   replace = TRUE
385 )

```