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

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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 CO_2 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 $MtCO_2e$, 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 CO_2e, 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.

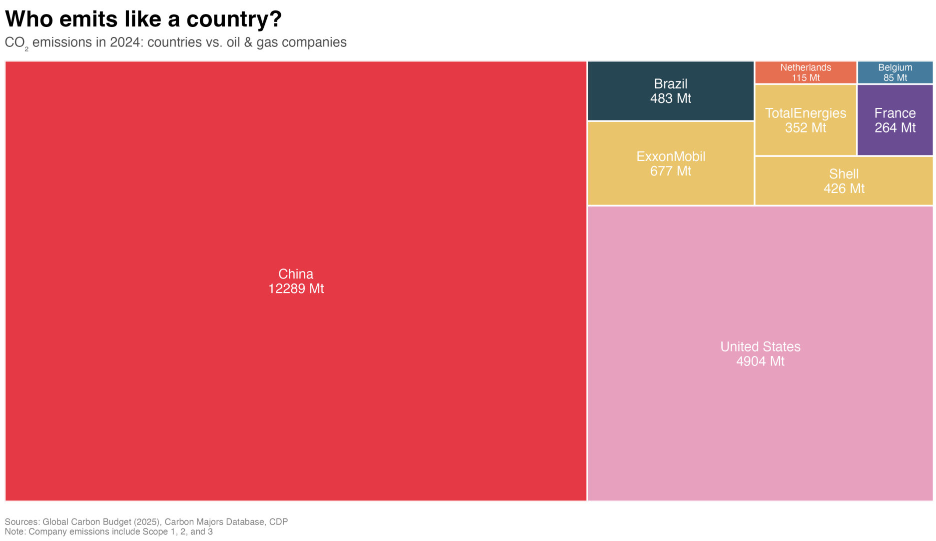

Figure 1: Annual CO_2 emissions (2024): selected countries and oil & gas companies from our sample.

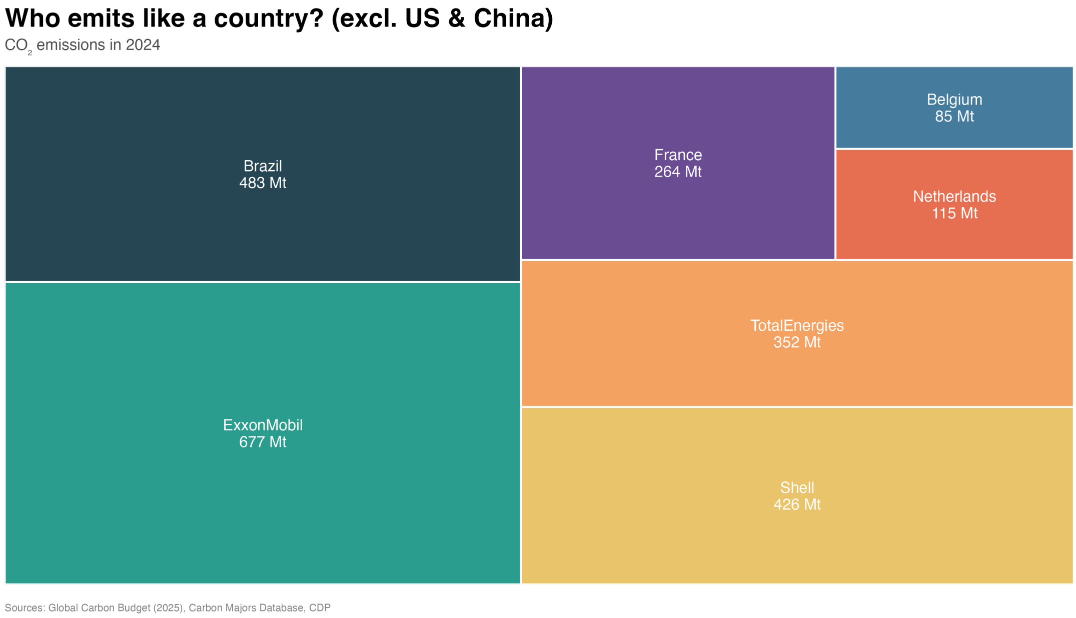

Figure 2: Annual CO_2 emissions (2024): selected countries (Without US and China) and oil & gas companies from our sample.

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:

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

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.

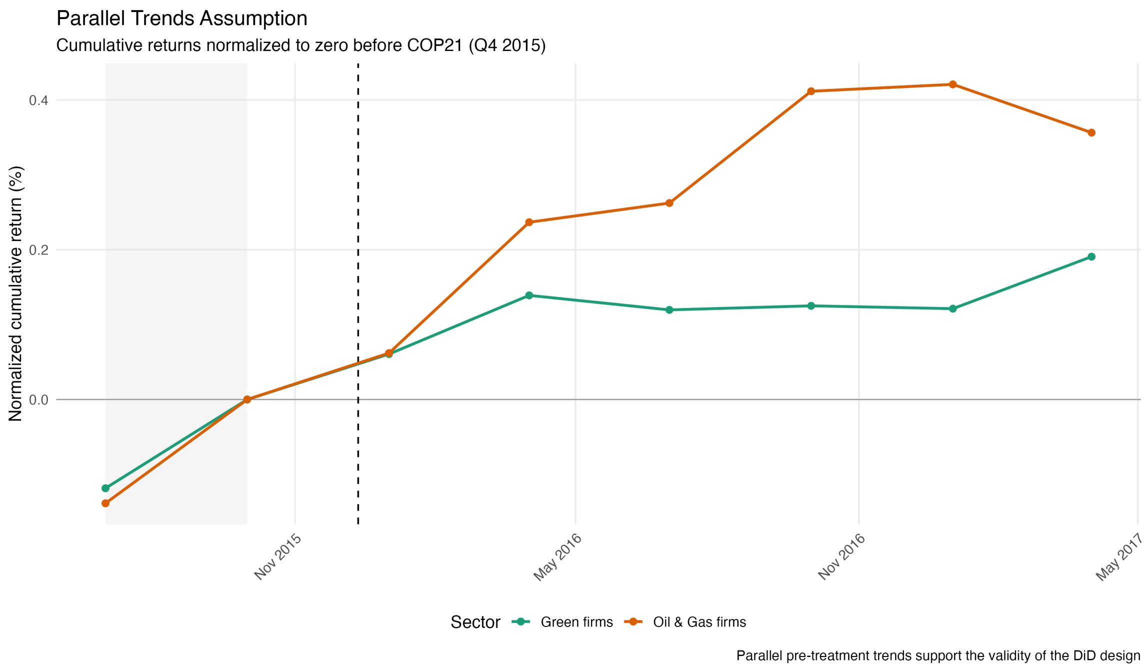

Figure 3: Parallel trends test. Quarterly cumulative returns normalized to zero at Q4 2015 (just before COP21).

6 Results

Table 2 presents the DiD estimation results across four specifications.

Dependent Variable:	Return			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	-0.024			
	(0.018)			
Green firm	0.085***			
	(0.025)			
Post-COP21	0.085***	0.085***		
	(0.025)	(0.025)		
Treatment × Post	-0.120***	-0.121***	-0.087**	-0.431***
	(0.034)	(0.034)	(0.034)	(0.076)
Treatment × Post × CountryAustralie				0.457***
				(0.101)
Treatment × Post × CountryBresil				0.449***
				(0.102)
Treatment × Post × CountryCanada				0.501***
				(0.102)
Treatment × Post × CountryChine				0.250**
				(0.105)
Treatment × Post × CountryFrance				0.307***
				(0.101)
Treatment × Post × CountryJapon				0.323***
				(0.102)
Treatment × Post × CountryUK				0.456***
				(0.101)
Treatment × Post × CountryUSA				0.343***
				(0.093)
Fixed-effects				
Ticker		Yes	Yes	Yes
YearMonth			Yes	Yes
Fit statistics				
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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Bolton, P. and Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, 142(2), 517–549.

Brooks, C. (2018). *Introductory Econometrics for Finance*, 2nd Edition. Cambridge University Press.

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 CO_2 emissions:** Carbon Majors Database — `emissions_low_granularity.csv` (`https://carbonmajors.org`)
- **Country CO_2 emissions:** Global Carbon Budget — `annual-co2-emissions-per-country.csv` (`https://ourworldindata.org/co2-emissions`)

Annex: Code

```
###############################################################################
# FINANCIAL ECONOMETRICS PROJECT
# Author : Yassine Mandengue
###############################################################################


###############################################################################
# PACKAGES
###############################################################################

library(tidyverse)
library(scales)
library(ggtext)
library(lubridate)
library(fixest)
library(treemapify)


###############################################################################
# PART I     MOTIVATIONAL DATA VISUALIZATION
# "Who emits like a country?"
###############################################################################

# ---------------------------------------------------------------------------
# 1. Data Import
# ---------------------------------------------------------------------------

emissions_low_granularity <- read_csv("Downloads/emissions_low_granularity.csv")

annual_co2_emissions_per_country <- read_csv(
  "Desktop/M2␣FIRE/Classes/Financial␣Econometrics␣and␣dataviz/Project/
␣␣␣annual-co2-emissions-per-country.filtered/
␣␣␣annual-co2-emissions-per-country.csv"
)


# ---------------------------------------------------------------------------
# 2. Country-Level Data Preparation
# ---------------------------------------------------------------------------
# - Select a subset of representative countries
# - Restrict the period to 2013  2024
# - Convert emissions from tonnes to million tonnes (MtCO2)

df_countries <- annual_co2_emissions_per_country %>%
  filter(
    Entity %in% c("United␣States", "China", "Brazil",
                  "France", "Netherlands", "Belgium"),
    Year >= 2013, Year <= 2024
  ) %>%
  transmute(
```

```r
    Year = Year,
    Entity = Entity,
    Emissions_Mt = round(`Annual CO emissions` / 1e6, 2)
  )


# ---------------------------------------------------------------------------
# 3. Company-Level Data Preparation
# ---------------------------------------------------------------------------
# - Focus on major oil & gas companies
# - Emissions already expressed in MtCO2e
# - Include Scope 1, 2 and 3 emissions

df_companies <- emissions_low_granularity %>%
  filter(
    parent_entity %in% c("ExxonMobil", "Shell", "TotalEnergies"),
    year >= 2013, year <= 2024
  ) %>%
  transmute(
    Year = year,
    Entity = parent_entity,
    Emissions_Mt = round(total_emissions_MtCO2e, 2)
  )


# ---------------------------------------------------------------------------
# 4. Merge Countries and Companies
# ---------------------------------------------------------------------------
# - Create a unified long-format dataset
# - Define entity type
# - Set factor order for stacked visualization

data_long <- bind_rows(df_countries, df_companies) %>%
  mutate(
    Type = case_when(
      Entity %in% c("United States", "China", "Brazil",
                    "France", "Netherlands", "Belgium") ~ "Country",
      TRUE ~ "Company"
    ),
    Entity = factor(
      Entity,
      levels = c(
        "China", "United States",
        "ExxonMobil", "Shell", "TotalEnergies",
        "Brazil", "France",
        "Netherlands", "Belgium"
      )
    )
  )


# ---------------------------------------------------------------------------
```

```r
# Treemap 5     DataViz F4A261
# ---------------------------------------------------------------------------
# Last year
latest_year <- max(data_long$Year)

treemap_data <- data_long %>%
  filter(Year == latest_year)

# --- Colors ---
colors_entities <- c(
  "China"          = "#E63946",
  "United States"  = "#E8A0BF",
  "ExxonMobil"     = "#2A9D8F",
  "Shell"          = "#E9C46A",
  "TotalEnergies"  = "#F4A261",
  "Brazil"         = "#264653",
  "France"         = "#6A4C93",
  "Netherlands"    = "#E76F51",
  "Belgium"        = "#457B9D"
)

colors_entities2 <- c(
  "China"          = "#E63946",
  "United States"  = "#E8A0BF",
  "ExxonMobil"     = "#E9C46A",
  "Shell"          = "#E9C46A",
  "TotalEnergies"  = "#E9C46A",
  "Brazil"         = "#264653",
  "France"         = "#6A4C93",
  "Netherlands"    = "#E76F51",
  "Belgium"        = "#457B9D"
)

p_tree_all <- ggplot(treemap_data, aes(
  area = Emissions_Mt,
  fill = Entity,
  label = paste0(Entity, "\n", round(Emissions_Mt), " Mt")
)) +
  geom_treemap(color = "white", size = 2) +
  geom_treemap_text(
    colour = "white",
    place = "centre",
    size = 12,
    grow = FALSE,
    reflow = TRUE
  ) +
  scale_fill_manual(values = colors_entities2) +
  labs(
    title = "Who emits like a country?",
    subtitle = paste0(" C O  emissions in ", latest_year, ": countries vs. oil &
       gas companies"),
```

```
    caption = "Sources:␣Global␣Carbon␣Budget␣(2025),␣Carbon␣Majors␣Database,␣CDP\nNote:␣Company␣emissions␣include␣Scope␣1,␣2,␣and␣3"
  ) +
  theme_minimal(base_size = 13) +
  theme(
    plot.title    = element_text(face = "bold", size = 20, margin = margin(b = 5)),
    plot.subtitle = element_text(size = 12, color = "gray30", margin = margin(b = 10)),
    plot.caption  = element_text(size = 8, color = "gray50", hjust = 0, margin = margin(t = 15)),
    legend.position = "none",
    plot.margin = margin(20, 20, 15, 15)
  )

p_tree_all

# ----------------------------------------------------------------------------
# Treemap 5.1     Without US and China
# ----------------------------------------------------------------------------

treemap_data_excl <- treemap_data %>%
  filter(!Entity %in% c("United␣States", "China"))

p_tree_excl <- ggplot(treemap_data_excl, aes(
  area = Emissions_Mt,
  fill = Entity,
  label = paste0(Entity, "\n", round(Emissions_Mt), "␣Mt")
)) +
  geom_treemap(color = "white", size = 2) +
  geom_treemap_text(
    colour = "white",
    place = "centre",
    size = 12,
    grow = FALSE,
    reflow = TRUE
  ) +
  scale_fill_manual(values = colors_entities) +
  labs(
    title = "Who␣emits␣like␣a␣country?␣(excl.␣US␣&␣China)",
    subtitle = paste0(" C O  ␣emissions␣in␣", latest_year),
    caption = "Sources:␣Global␣Carbon␣Budget␣(2025),␣Carbon␣Majors␣Database,␣CDP"
  ) +
  theme_minimal(base_size = 13) +
  theme(
    plot.title    = element_text(face = "bold", size = 20, margin = margin(b = 5)),
    plot.subtitle = element_text(size = 12, color = "gray30", margin = margin(b = 10)),
    plot.caption  = element_text(size = 8, color = "gray50", hjust = 0, margin = margin(t = 15)),
```

```r
    legend.position = "none",
    plot.margin = margin(20, 20, 15, 15)
  )

p_tree_excl


##############################################################################
# PART II     STOCK RETURNS AND PARALLEL TRENDS
##############################################################################

# ---------------------------------------------------------------------------
# 1. Stock Prices and Metadata
# ---------------------------------------------------------------------------

prices <- read_csv("stock_prices.csv") %>%
  mutate(Date = as.Date(Date))

metadata <- read_csv("companies_metadata.csv") %>%
  mutate(Treatment = ifelse(Sector == "Green", 1, 0))


# ---------------------------------------------------------------------------
# 2. Long Format and Cleaning
# ---------------------------------------------------------------------------

prices_long <- prices %>%
  pivot_longer(cols = -Date, names_to = "Ticker", values_to = "Price") %>%
  filter(!is.na(Price)) %>%
  arrange(Ticker, Date) %>%
  left_join(metadata, by = "Ticker") %>%
  filter(!is.na(Sector))


# ---------------------------------------------------------------------------
# 3. Return Computation
# ---------------------------------------------------------------------------
# Returns are computed over the full sample to ensure precision.

returns_data <- prices_long %>%
  group_by(Ticker) %>%
  arrange(Date) %>%
  mutate(
    Return = (Price / lag(Price) - 1) * 100,
    Log_Return = log(Price / lag(Price)) * 100
  ) %>%
  ungroup() %>%
  filter(!is.na(Return))


# ---------------------------------------------------------------------------
# 4. Event Window Around COP21
```

```r
# ----------------------------------------------------------------------------

returns_data_filtered <- returns_data %>%
  filter(Date >= "2015-07-01" & Date <= "2017-06-30")

cop21_date <- as.Date("2015-12-12")


# ----------------------------------------------------------------------------
# 5. Parallel Trends    Quarterly Aggregation
# ----------------------------------------------------------------------------

quarterly_returns <- returns_data_filtered %>%
  mutate(Quarter = floor_date(Date, "quarter")) %>%
  group_by(Quarter, Sector) %>%
  summarise(Mean_Return = mean(Return, na.rm = TRUE), .groups = "drop")

quarterly_cumulative <- quarterly_returns %>%
  arrange(Sector, Quarter) %>%
  group_by(Sector) %>%
  mutate(Cumulative_Return = cumsum(Mean_Return)) %>%
  ungroup()

# Normalization at Q4 2015 (just before COP21)
baseline_quarter <- as.Date("2015-10-01")

baseline_values <- quarterly_cumulative %>%
  filter(Quarter == baseline_quarter) %>%
  select(Sector, Baseline = Cumulative_Return)

quarterly_normalized <- quarterly_cumulative %>%
  left_join(baseline_values, by = "Sector") %>%
  mutate(Normalized_Return = Cumulative_Return - Baseline)


# ----------------------------------------------------------------------------
# 6. Parallel Trends Visualization
# ----------------------------------------------------------------------------

plot_parallel_trends <- ggplot(
  quarterly_normalized,
  aes(x = Quarter, y = Normalized_Return, color = Sector)
) +
  annotate("rect",
           xmin = min(quarterly_normalized$Quarter),
           xmax = baseline_quarter,
           ymin = -Inf, ymax = Inf,
           fill = "grey90", alpha = 0.4) +
  geom_hline(yintercept = 0, color = "grey60", linewidth = 0.4) +
  geom_vline(xintercept = cop21_date, linetype = "dashed") +
  geom_line(linewidth = 1) +
  geom_point(size = 2) +
```

```
  scale_color_manual(
    values = c("Green" = "#1B9E77", "Oil_Gas" = "#D95F02"),
    labels = c("Green" = "Green firms", "Oil_Gas" = "Oil & Gas firms")
  ) +
  scale_x_date(date_breaks = "6 months", date_labels = "%b %Y") +
  labs(
    title = "Parallel Trends Assumption",
    subtitle = "Cumulative returns normalized to zero before COP21 (Q4 2015)",
    y = "Normalized cumulative return (%)",
    x = NULL,
    caption = "Parallel pre-treatment trends support the validity of the DiD design"
  ) +
  theme_minimal(base_size = 13) +
  theme(
    legend.position = "bottom",
    panel.grid.minor = element_blank(),
    axis.text.x = element_text(angle = 45, hjust = 1)
  )

plot_parallel_trends


##############################################################################
# PART III     DIFFERENCE-IN-DIFFERENCES ESTIMATION
##############################################################################

did_data <- returns_data %>%
  mutate(
    Post = ifelse(Date >= cop21_date, 1, 0),
    DiD = Post * Treatment,
    YearMonth = floor_date(Date, "month")
  )


# ---------------------------------------------------------------------------
# DiD Models
# ---------------------------------------------------------------------------

# Model 1: Simple DiD (OLS)
model1 <- feols(Return ~ Treatment + Post + DiD, data = did_data)
summary(model1)

# Model 2: DiD with firm fixed effects
model2 <- feols(Return ~ Post + DiD | Ticker, data = did_data)
summary(model2)

# Model 3: DiD with firm and time fixed effects
model3 <- feols(Return ~ DiD | Ticker + YearMonth, data = did_data)
summary(model3)

# Model 4: Heterogeneous effects by country
```

```
model4 <- feols(Return ~ DiD * Country | Ticker + YearMonth, data = did_data)
summary(model4)



# ============================================================================
# EXPORT PLOTS
# ============================================================================

ggsave("ptree_all.png", p_tree_all, width = 12, height = 7, dpi = 300)
ggsave("ptree.png", p_tree_excl, width = 12, height = 7, dpi = 300)
ggsave("parallel_trend.png", plot_parallel_trends, width = 12, height = 7, dpi = 300)



# ============================================================================
# EXPORT DiD RESULTS TO LATEX TABLE
# ============================================================================

etable(
  model1, model2, model3, model4,
  tex = TRUE,
  file = "did_results.tex",
  title = "Difference-in-Differences Estimation Results",
  dict = c(
    Treatment = "Green firm",
    Post = "Post-COP21",
    DiD = "Treatment $\\times$ Post"
  ),
  se.below = TRUE,
  digits = 3,
  fitstat = ~ n + r2,
  replace = TRUE
)
```