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Are financial markets aligned with climate action? New Evidence from the Paris Agreement

Tobias Kruse* Myra Mohnen† Misato Sato* ‡

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Abstract

It is increasingly recognised that financial markets have a key role to play in meeting climate mitigation objectives. But are markets willing to direct more capital allocation towards such a low carbon pathway? This paper provides new evidence that financial markets value firms' expansion into production of low carbon goods and services, but they remain cautious on divesting from the most polluting industries. We exploit the Paris Agreement as an exogenous political shock that signalled increased global commitment on climate action. Using an event study approach, we examine the daily stock prices of major publicly listed US companies. We distinguish green and brown firms using their green revenue share and their carbon intensity respectively. We find evidence that the cumulative returns of stocks for firms are re-priced during the five days following the Paris Agreement. Cumulative returns are up to 10% higher for green firms while the effect is less pronounced for brown firms and limited to firms active in the oil and gas extraction. Overall, our results suggest that capital markets are responding to opportunities but less to risks in the low carbon economy.

Keywords: Green growth; Green revenues; Event Study; Paris Agreement; Firm value; GHG emissions.

JEL Classification: G14; O16; Q56; Q58

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1 Introduction

Mobilising investments in low-carbon technologies and capital assets is key to tackling climate change. The Intergovernmental Panel on Climate Change (IPCC) report showed that an annual $1.6 to 3.8 trillion investment in energy systems is needed to keep global warming within a 1.5 degree scenario and avoid the most harmful effects of climate change (Rogelj et al., 2018). Climate investments were estimated at around $500 billion in 2017, 54% of which is derived from the private sector (Climate Policy Initiative, 2018). Therefore, a significant increase in investments is required to meet these goals.

Numerous initiatives testify to the increasing awareness and urgency to bring about changes in financial market practices, norms and behaviour to ensure capital flows towards low carbon investments. Under the Paris Agreement, countries have collectively pledged to make "financial flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development" (United Nations, 2015). The European Commission adopted an action plan on climate finance in 2018 which focuses on improving transparency for example by establishing taxonomy for firms' sustainable activities and labelling for green financial products (European Commission, 2018). Global private sector initiatives have also been launched, such as the Task Force on Climate-related Financial Disclosures which promotes consistent climate-related financial risk disclosures to meet investors' information needs.

In this paper, we ask whether global capital markets are indeed responding to the low carbon objective. Do investors back companies that are developing and adopting low carbon technologies or managing climate related risks and opportunities? Do inventors divest away from polluting firms? Determining whether and to what extent the provision of public goods (or bads) by firms is privately rewarded (or punished) is important to assess the market failures that policy makers are confronted with. However, there is a lack of robust evidence due to two main reasons. First, observing and quantifying firms' environmental performance and the degree to which it positively contributes to the environment is difficult due to data limitations. Researchers have previously relied on crude proxies that are often discrete and self-reported in nature. For example, green firms have been identified based on sustainability stock indices (e.g. Oberndorfer et al., 2013), the voluntary membership to an environmental programme (e.g. Fisher-Vanden and Thorburn, 2011), the voluntary adoption of environmental management standards (e.g. Cañon-de Francia and Garcés-Ayerbe, 2009) and environmental certification (e.g. Jacobs et al., 2010).[1] Second, it is difficult to capture a firm's efforts on the commercial side to develop new, cleaner goods and services in response to changing customer preferences. Most of the measures of firms' environmental performance previously used, capture internally-driven pollution abatement efforts to reduce the environmental impact of firms' own operations.[2] Finally, the existing

[1] Accurately measuring environmental performance is an inherently difficult task because all human and economic activities have an impact on the environment, and there is a lack of a precise and widely accepted framework for defining and measuring efforts to reduce environmental impact and production of goods and services that have a positive environmental outcome (OECD and Eurostat, 1999).

[2] Ambec and Lanoie (2008) distinguish two channels through which environmental innovation can impact firms' environmental and economic performance: the "cost channel" whereby firms reduce input costs through improving efficiency and mitigating risk, and the"revenues channel" whereby firms increase revenue by developing

indicators of firms' environmental performance are limited in terms of sectoral and geographic coverage and scope. The small sample sizes and the limited variation in the environmental performance indicators present external validity issues and pose difficulties in teasing out the direction of causality between shifts into or away from environmental activities and market performance.[3]

We overcome these empirical issues by constructing a new dataset for publicly listed US firms. We combine several datasets: daily stock prices from the Center for Research in Security Prices (CRSP), annual reports of firms from the financial services company *FTSE Russell*, patents from the World Patent Statistical Database (PATSTAT) and emission intensity from *Trucost Carbon Metrics*. In addition to the market valuation of a firm, our novel dataset allows us to measure firms' environmental performance based on green revenues, low-carbon patenting activities (from Dechezleprêtre et al. (2017)), and carbon emissions. These three different measures have several advantages over measures previously used in the literature. First, these measure are objective in nature and consequently are more likely to reflect real effort. Moreover, the measure based on the green revenue share allows us to explore the capital market effects of firms' environment-focused *commercial* activities, filling an important evidence gap on the investors' perception of growth opportunities for green markets. Second, we can examine both positive and negative environmental activities of firms over time, and therefore distinguish between "green" and "brown" firms. We assess the market response to both the risks and opportunities in the low carbon economy. Third, these measures are continuous thus allowing us to quantify the degree to which firms are diversifying into low carbon markets over time. We can therefore look at both the intensive and extensive margins. Finally, our rich dataset covers a broad category of sectors, acknowledging the fact that environmental goods and services are provided not only by firms belonging to the narrowly defined environmental sector. Our baseline sample includes information on over 5,000 publicly listed firms in the US, representing 98 per cent of US market capitalisation. Of these, we identify over 250 firms that generate some revenue from the production and sales of environmental goods and services, and over 370 firms that have filed "clean" patents in the study time period.

To examine capital market responses to firms' environmental activities, we examine the Paris Agreement, signed on the 12 December 2015, which marked a global commitment to the environment. The Paris Agreement and the preceding negotiation was a major event with global scope and significant media coverage. The final agreement contained important elements of surprise, most noteworthy the inclusion of the more ambitious 1.5 degree target and the unanimity of the agreement including all emerging and developing economies. Through an event study we assess the causal effects of this positive environmental event on stock prices.[4] Specifically we use a

new, cleaner products.

[3]Both the propensity of firms to undertake environmental protection, and how such effort is valued by the stock market may vary by sector, for example due to the role of technology or policies. Most studies have focused on investors response in particular sectors most affected by climate and energy i.e. fossil fuels (e.g. Mukanjari and Sterner, 2018; Sen and von Schickfus, 2019), chemicals (e.g. Capelle-Blancard and Laguna, 2010) and renewables (e.g. Mukanjari and Sterner, 2018; Aklin, 2018).

[4]A key advantage of using event study methodology over regression or portfolio analyses is that it allows estimating causal effects. Most papers examining the link between environmental performance and market valuation of firms or portfolios of firms use regression analysis (e.g. Moliterni, 2018). Isolating effects of environmental per-

three-factor Fama-French model to estimate abnormal returns more reliably than the one-factor model (Fama and French, 1993, 1996; Hussain et al., 2002; Kolari and Pynnonen, 2010). Combining this with Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model estimation allows us to deal with serial heteroskedasticity of returns. We test for abnormal returns in the period leading up to and following the Paris Agreement, to evaluate whether stronger (weaker) environmental performance leads to higher (lower) market valuation. We construct deciles of green and brown firms using our indicators of environmental performance. If stock markets do not penalise or value firms' environmental efforts, then we would expect that the effect of the Paris agreement on abnormal returns across the deciles are not statistically different from zero and one another.

We find evidence that stock markets re-price firms that are engaged in the commercialization of green goods and services, but they do not always re-value brown firms. Firms in the greenest decile in terms of green revenue share significantly outperformed the market in the week following the Paris Agreement. We identify a level shift in green firms' market capitalisation following the agreement. The sample of the greenest firms observed on average 10% higher returns for the post-event period (days 0-5) compared to the overall market. This is equivalent to a relative increase of approximately 200 million USD in market capitalisation per firm, or a total relative increase of 12.6 billion USD in market capitalisation across the 63 greenest firms. We find evidence of both intensive and extensive margin effects. We find significant differences between the greenest firms and less green firms. In contrast, market responses to the agreement are indistinguishable between firms with high and low carbon intensity firms. The exception is in the higher carbon intensive firms in the oil and gas extraction sector, where negative but marginally significant abnormal returns are observed. We perform a number of robustness checks. We look at an alternative measure of a firm's environmental effort by using green patent share. We also explore our results in different sectors and across different event windows. We confirm the validity of the event study approach by checking for confounding events using news search. We also look at the surprise element of the event by checking trade volumes in futures.

There is a rich empirical literature looking at investors' valuation of firm's environmental performance. These studies span across multiple disciplines including accounting, business, finance, industrial ecology and environmental economics. However, these studies often reveal conflicting results. Nonetheless the literature has offered a number of important insights. One first insight is that results vary depending on the environmental performance indicator. Studies in the accounting and finance literatures ask which indicators of environmental performance are economically relevant in valuation models. Jacobs et al. (2010) suggests markets are selective in the type of environmental performance measures.[5] Gilley et al. (2000) instead finds that markets react more favourably to product-driven environmental initiatives than process-driven, while Konar and Cohen (2001) argues that objective measures of environmental performance should be used to evaluate capital market responses. Studies using pollution level generally find

formance on stock prices is difficult with regression analysis because preferences for investing in green or brown firms is endogenous and there are many other factors influencing decision making in financial markets.

[5] They find for example that markets react positively to announcements on philanthropic gifts and environmental certifications but negatively to voluntary emission reductions, though in aggregate environmental initiatives and awards cause no significant effect on stock prices.

that higher pollution levels are associated with lower market valuation, suggesting that investors expect tightening of environmental regulation and perceive current pollution as unbooked liabilities (King and Lenox, 2001; Konar and Cohen, 2001; Matsumura et al., 2014). Studies that use measures based on third-party assessments, particularly those that are discrete in nature, often find conflicting results. Curran and Moran (2007) find no statistically significant effects from a firm experiencing inclusion in, or deletion from, the FTSE4Good UK50 Index. Lourenço et al. (2012) find that that markets penalise large profitable non-green firms that are excluded from the Dow Jones sustainability index. Oberndorfer et al. (2013) in contrast finds that the market penalises green firms included in the Dow Jones sustainability stock index. Their sample of 30 German firms - analysed between 1999 and 2002 - experience on average a relative decrease of stock returns after being included in the sustainability index. We contribute to the debate by providing the first study using three different objective and continuous measures of environmental performance. Our rich dataset allows us to not only distinguish between green and brown but also the intensive and extensive margins. Our results highlight that investors distinguish between green and brown firms. Moreover, we show that the extensive as well as the intensive margin of firms' green revenue share matter for investors.

Another insight from the previous literature is that the market values firms' environmental performance differently depending on the time period, the size of firm and the intensity of the polluting activity of the firm. For instance, Moliterni (2018) disaggregates year-by-year effects and shows that a positive relationship between firms' environmental performance and market valuation is more likely to be found in studies looking at more recent years. This suggests that environmental sustainability has gained importance over time in the investment community with the rise of ethical investing. Lourenço et al. (2012) shows that the penalty for poor environmental performance on firm value is more pronounced for large, profitable firms, and argues this is because of the greater public scrutiny and pressures from stakeholders they receive, and the expectation of leadership over sustainability and innovation they carry. In a study on the US Pulp and Paper sector, Clarkson and Li (2004) finds that markets place a positive value on environmental capital expenditure for low-polluting firms that over-comply with existing regulations, whereas there is no effect for high-polluting firms (measured using toxic release data). Abatement expenditures create no value for high-polluting sectors because it reflects unbooked liabilities that they will incur in the future, whereas higher abatement expenditure in low-polluting firms (with limited obligations) signals innovation and confidence. Our analysis uncovers another source of heterogeneity based on sectors.

Closely related papers are those of Capelle-Blancard and Laguna (2010), Aklin (2018) and Mukanjari and Sterner (2018). Capelle-Blancard and Laguna (2010) estimates that the market value of firms with chemical plants and refineries worldwide declines on average by 1.3% over the two days immediately following explosions. Aklin (2018) and Mukanjari and Sterner (2018) use the election of Donald Trump in the US presidential election in 2016 as an unexpected event. The latter study also tests the effects of the signing of the Paris Agreement in December 2015. They estimate the impact on coal and renewable energy Exchange Traded Funds (ETFs), finding no significant effects on coal or renewable energy ETFs except for a positive effect of the

Paris Agreement on solar energy. They argue that the coal industry has already been declining in many countries due to cheaper substitutes, increased energy efficiency or slowing growth in coal consuming countries, so that investment has already started to shift away from coal prior to the agreement. We add to these studies by showing that the Paris Agreement did have a significant effect for the valuation of green firms.

The remainder of this paper is structured as follows. In Section 2 we discuss the events surrounding the Paris Agreement. Section 3 explains the methodology and Section 4 describes the different data sets we use for our analysis. Section 5 presents our results. In Section 6, we conclude.

2 The Paris Agreement

The Paris Agreement was signed on 12 December 2015 by the Parties to the United Nations Framework Convention on Climate Change (UNFCCC) at the 21st Conference of the Parties (COP 21), and marked a landmark global commitment to combat climate change and to accelerate and intensify the actions and investments needed for a sustainable low carbon future.[6] We exploit this significant event as a discrete and exogenous shock that shifted public perception. Using an event study strategy, we assess the effects of environmental performance on stock performance. Specifically, we test if, following the agreement, revaluation of stocks are heterogeneous across portfolios of firms with different stakes or risks in the low carbon economy.

An important assumption in event studies is that the event is exogenous and has an element of surprise. If fully anticipated, no abnormal returns are expected as valuations would already reflect expectations according to the efficient market hypothesis. Success at Paris was to some extent anticipated, yet the outcome turned out surprisingly better than anticipated. In advance of the the COP-21, already in 2014, the US and China already made a joint announcement on climate change to work constructively together to mitigate climate change.[7] These announcements already included emission-reduction pledges from both countries. It was considered to be a major milestone in increasing the likelihood that a global agreement could be passed in Paris.

Examining the coverage in public liveblogs and newsfeeds during the two-week negotiation period reveals there was a high degree of uncertainty around whether an agreement would actually

[6] Compared to previous climate summits, the Paris Agreement adopted a new strategy allowing countries to set their own targets (Nationally Determined Contributions or NDCs) in combination with an international review process that scrutinised the ambitions of individual pledges. This "pledge and review" process determined the actual ambition of the agreement and encouraged countries to gradually strengthen their targets. The Paris Agreement therefore shifted away from requiring mandatory emissions reductions from countries, which had been a major barrier in past negotiations, and likely provided a breakthrough in the negotiation process (Falkner, 2016). In addition to agreeing on the NDC approach and the submission of reduction targets, the international community also agreed to making international "finance flows consistent with a pathway towards low greenhouse gas emissions and climate resilient development" (UNFCCC, 2016, p.22). Thus, the ambition of the agreement goes beyond emission reductions and aims to redirect and restructure financial flows towards a low-carbon and climate resilient economy.

[7] See for example this article in the Guardian (Taylor and Branigan, 2014):`https://www.theguardian.com/environment/2014/nov/12/china-and-us-make-carbon-pledge`, or the statement provided by the Obama Administration (The White House, 2014):`https://obamawhitehouse.archives.gov/the-press-office/2014/11/11/us-china-joint-announcement-climate-change`.

be reached. Indeed, the agreement was scheduled to be passed on Friday 11 December, but negotiations continued until Saturday 12 December. On the Friday (last trading day prior to the signing), there was still considerable uncertainty around ambition, unanimity and final wording. For example, it was unclear if the long term temperature goal of 1.5°C would be included instead of the more lenient 2°C. In particular, the positions of large oil producing states like Saudi Arabia was also uncertain. During overnight negotiation sessions between Thursday 10 and Friday 11, Saudi Arabia stepped up its opposition against the 1.5°C target, arguing that the science is not entirely conclusive. This objection risked that the more ambitious 1.5°C target could be adopted unanimously. The positions of large emerging economies also remained unclear. The Indian Environment Minister gave a press conference on Friday 11 at around 4pm (CET) saying that there would still be a "long road ahead" if there was not more effort from the developed nations and that the likelihood of passing the agreement hang in balance (ClimateHome, 2015). Brazil joined the "coalition of high ambition" (also known as the "progressive alliance") only at around 4:30pm (CET) on Friday 11. This was considered a potential game changer, as it was the first large emerging country to join this coalition. This raised expectations that it would become a bridge builder towards the other large emerging economies to increase their ambition.[8] The Paris Agreement also represents a good event to study in this context because it marks a major global event with wide media coverage that would not go unnoticed to investors. In addition, we show that there are no major confounding events that coincides with signing of the Paris Agreement, in Section 5.4.

3 Event study design

Event studies are used to estimate so-called "normal" and "abnormal returns", which are estimated from capital asset pricing models (CAPM). They are commonly applied to examine the effect of mergers and acquisitions, earnings announcements, or the effect of new regulation (MacKinlay, 1997).[9] The most basic approach is the one-factor model based on the CAPM for a firm or stock i on day t (i=1,..., N; t=1,...,T) ((Brown and Warner, 1980; Campbell et al., 1997))

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \epsilon_{it} \tag{1}$$

where r_{it} is the return for share i, and r_{mt} is the return of the market portfolio at the end of day t. The risk-free interest rate at the beginning of period t is expressed by r_{ft}, and ϵ_{it} is the error term with expectation $E(\epsilon_{it}) = 0$ and variance $Var(\epsilon_{it}) = \sigma^2_{\epsilon_i}$. The term $(r_{it} - r_{ft})$ on the left hand side is also referred to as the excess return r^e_{it} , and $r_{mt} - r_{ft}$ as the index excess

[8] See for example the Guardian liveblog on 11 December 4:30pm (CET) from the Paris negotiations (Vaughan, 2015)

[9] We focus on short-term event studies since they are considered to be more robust compared to long-term studies. Long-term studies typically examine event-horizons over multiple years (e.g. Lyon et al. (1999)). Long-term event studies are methodologically similar to portfolio analyses, which typically compare the development of returns over multiple years (e.g. Mollet and Ziegler (2014)). Trade-offs exists in the respective approaches. While portfolio analyses can provide insight into the relative performance of stock returns over long time horizons they can typically not establish causality.

return r^e_{mt} (with respect to the risk-free rate). All returns are defined as logarithmic returns. The parameters α_i, β_i are unknown and estimated by the model. The normal (excess) returns $E(r_{it} - r_{ft})$ are unknown and defined as the expectation of (excess) returns without conditioning on the event. Abnormal returns (AR) are defined as the difference between the observed and the normal (excess) returns (Oberndorfer et al., 2013):

$$AR_{it} = (r_{it} - r_{ft}) - E(r_{it} - r_{ft}) \tag{2}$$

While this one-factor market model for abnormal returns is the simplest approach, many studies show that the three-factor model developed by (Fama and French, 1993) has more explanatory power and also shows desirable characteristics for robust statistical inference (Fama and French, 1993, 1996; Hussain et al., 2002; Kolari and Pynnonen, 2010).[10] The three-factor model includes two additional terms SMB_t and HML_t. The former is called the small-minus-big market capitalisation factor return. The latter is referred to as the high-minus-low book-equity/market-equity factor return at day t. The rationale for the SMB factor is that stocks with small market capitalisations tend to outperform the market. The HML factor adjusts for the finding that so called value stocks, which are stocks with a low market valuation relative to its fundamentals (measured by price-to-earnings or price-to-book ratio among others), also tend to outperform the market. Including these two factors allows to control for this systematic outperformance. Fama and French (1993) show that these additional terms are particularly well-suited to capture common variation in stock returns (for further details on these factors see Fama and French (1993)).[11] All of the models require the underlying assumptions that there is an element of surprise in the event and that there are no other confounding events occurring.

In the 3-factor model, the abnormal returns are obtained as the difference between the realised and predicted returns on day t in the event period.

$$\widehat{AR}_{it} = r^e_{it} - \left(\hat{\alpha}_i + \hat{\beta}_{i1} r^e_{mt} + \hat{\beta}_{i2} SMB_t + \hat{\beta}_{i3} HML_t\right) \tag{3}$$

To estimate the 3-factor model using GARCH, we additionally use information on previous returns as well as previous volatility of individual shares and the overall market. Excess returns

[10] By including the additional two factors the Fama French model reduces cross-sectional correlation between shares substantially (Kolari and Pynnonen, 2010), which is important for correct inference in particular in the context of event day clustering.

[11] The daily Fama-French factors, are constructed using 6 value-weight portfolios formed on size and the book-to-market ratio. The SMB factor is constructed by subtracting the average return of the three "large portfolios" consisting of large firms according to their market equity, from the average return of the three portfolios containing small firms (according to their market equity). The HML factor is constructed by subtracting the average returns of the two growth portfolios from the two value portfolios. The growth and value portfolio is constructed based on the ratio of book equity to market equity (BE/ME). Firms in the top 30% of BE/ME are included in the growth portfolios. Firms with a BE/ME ratio in the bottom 70% are included in the value portfolio. The portfolios include all NYSE, AMEX and NASDAQ stocks (Information taken from Kenneth French's website: `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.)

are then defined as (Engle, 2001; Savickas, 2003; Pynnonen, 2004):

$$r_{it}^e = \alpha_i + \beta_{i1} r_{mt}^e + \beta_{i2} SMB_t + \beta_{i3} HML_t + \eta_{it} \qquad \eta_{it}|\Omega_t \sim N(0, h_{it}) \tag{4}$$

$$h_{it} = a_i + b_i h_{it-1} + c_i \eta_{it-1}^2 \tag{5}$$

where $\alpha_i, \beta_{i1}, \beta_{i2}, \beta_{i3}, a_i, b_i, c_i$ are parameters to be estimated. Ω_t is the information set that is available at time t, which includes current and previous returns $r_{i,u}$ and $r_{m,u}$ for all $u \leq t$, and current and previous volatility- $h_{i,u}$, and error estimates $\eta_{i,u}$ for $u \leq t$ (Engle, 2001; Savickas, 2003; Pynnonen, 2004).

The estimated abnormal returns can be aggregated cross-sectionally and over multiple event days. Our estimated average abnormal returns (AAR) over the cross-section of N firms are defined as (Khotari and Warner, 2006):

$$\widehat{AAR}_t = \frac{1}{N} \sum_{i=1}^{N} \widehat{AR}_{it} \tag{6}$$

Aggregating these estimated average abnormal returns over multiple event days (starting at time t_1 through time t_2) results in our estimated cumulative average abnormal returns (CAAR)

$$\widehat{CAAR}_{t_1,t_2} = \sum_{t=t_1}^{t_2} \widehat{AAR}_t \tag{7}$$

Figure 1 illustrates the stylised time line of event studies. The "estimation period" is used to generate predictions of returns for the event period. These predictions capture the returns in the non-observed potential outcome that the event had not taken place. Abnormal returns are then estimated for each firm i in the "event window" by comparing the observed returns relative to the predicted counterfactual. If the estimation window is sufficiently large the estimated abnormal returns are approximately normally distributed with expectation zero and variance $\sigma_{\epsilon_i}^2$. The event window is typically defined as beginning twenty days prior to the event, to reduce bias from anticipation, and ending up to ten days after the event ($t_{-20,10}$) (Oberndorfer et al., 2013; Sen and von Schickfus, 2019). Defining the event window up to 10 days after the agreement is a relatively long time period, as stock markets absorb every day vast amounts of information. It however also allows us to show that any abnormal returns do not remain significantly different from the market, which would raise concerns of market efficiency and the choice of firms in our portfolios. Abnormal returns measure the difference between realised and predicted stock returns, and capture whether a portfolio of shares has outperformed the market over a period of time. However, extended periods of non-zero abnormal returns are inconsistent with the efficient market hypothesis because traders constantly look for such arbitrage opportunities (Campbell et al., 1997; Khotari and Warner, 2006). If investors increase their investment into a particular stock that has experienced abnormal returns, the price of the stock rises, which in turn reduces future returns. In line with the existing literature (Fisher-Vanden and Thorburn, 2011; Oberndorfer et al., 2013; Griffin et al., 2015) we define the estimation window to be the one hundred days prior to the event window ($t_{-121,-21}$). The event day t_0 is defined as the first trading-day at which the event becomes effective (MacKinlay, 1997). In our case this is Monday 14 December (day 0 in the event analysis), the first trading day following the agreement (See timeline of negotiation process in Section 3).

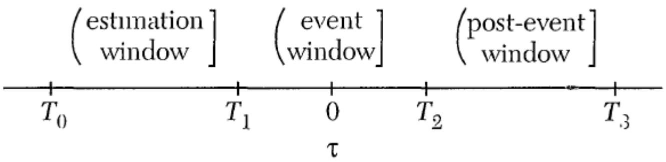


Figure 1: Time line for an Event Study (from MacKinlay (1997))

Note: This figures shows schematically the estimation, event, and post-event windows.

Instead of using OLS to estimate the 3-factor Fama-French model, we use a more robust Generalised AutoRegressive Conditional Heteroskedasticity (GARCH) model (Bollerslev, 1986; Engle, 2001; Savickas, 2003). One concern for correct inference in event studies is that the variances of the returns are time varying with some degree of autocorrelation, which is not accounted for in OLS models. Financial markets are prone to conditional heteroskedasticity, as upward or downward price spikes can trigger automated response orders, which are commonly used to manage risks among investors. Price spikes can therefore induce additional volatility, which is serially correlated, or in other words conditional on periods with elevated variance. GARCH models consider a varying conditional variance and are therefore able to deal with such serial heteroscedasticity by using past values of the variance. More specifically GARCH uses autoregressive lags and moving average lags of the variance to absorb the effects of conditional heteroskedasticity (Kolari and Pynnonen, 2010, 2011). The GARCH(p,q) model is a generalised model, in which p and q indicate the order of autoregressive terms in the model. The GARCH(1,1) model is a specific case commonly applied in financial time series. It considers one autoregressive lag and one moving average lag. We use GARCH(1,1) models throughout the analysis.

Following Sen and von Schickfus (2019), we report our main results in 3-day "rolling" cumulative average abnormal returns (CAARs), which cover the 3-day window centred around the respective median day [12]. For instance, the calculation of the rolling 3-day CAAR on day one employs the abnormal returns from the days zero, one and two.[13] The advantage of using rolling window approach is that it shows the gradual change in the CAARs thus shows more variation in the data compared to a 5-day analysis window, for example. We also report and discuss results on 5-day CAARs following Oberndorfer et al. (2013), to quantify the magnitude of the effects

[12] 3-day windows are also used by Kogan et al. (2017) among others

[13] The statistical inference tests are applied to each point estimate for rolling and non-rolling event windows. For instance, the confidence interval around the 3-day rolling CAAR estimate on day 2, shows the level of statistical significance of the cumulative average abnormal return of the point estimate that employs the event days one, two and three.

over the entire post-event period (Figures G.1 and G.2 in the Appendix). In general, inference based on CAARs reduces the possibility of incorrect rejection of a true null hypothesis (of no difference) (type I error) but increases the possibility of failing to reject a false null hypothesis (of no difference) (type II error) (Sen and von Schickfus, 2019).[14]

The null hypothesis of event studies is that the event has no effect on excess returns. To test this hypothesis we use the commonly used nonparametric Corrado (1989) rank test with the aggregation approach by Cowan (1992) for cumulative average abnormal returns (CAARs), which implicitly accounts for cross-sectional correlations across firms (Kolari and Pynnonen, 2010; Oberndorfer et al., 2013).[15] One advantage of nonparametric tests over parametric tests such as the Patell (1976) and Boehmer et al. (1991) (also known as the BMP test) is that they do not rely on distributional assumptions of abnormal returns. Since stock prices are typically not normally distributed, nonparametric tests have become the most commonly used test statistics (Kolari and Pynnonen, 2011). As a robustness check we also use parametric tests, in particular the commonly used BMP (Boehmer et al., 1991) test as well as the parametric KP test, developed by Kolari and Pynnonen (2010). One concern in event studies is that the cross-sectional variation in the true abnormal returns results in variance increases around the event (also called event-induced volatility). This may bias commonly used parametric tests towards rejecting the null hypothesis (such as the Patell (1976), or Brown and Warner (1985) tests). Harrington and Shrider (2007) show that among the parametric tests, the BMP test is robust to such an event induced increase in volatility.[16] Furthermore, we also use the KP test statistic, which further modifies the BMP-test statistic to account for cross-correlation in abnormal returns. We report results using the nonparametric Corrado test in the main part of the paper. Results using the BMP, and KP test statistics are reported in the Appendix in Figures H.1 & H.2, and I.1 & I.2.

Event Studies with Partial Anticipation

We argued in Section 2 that the Paris Agreement contained an element of surprise. However, the surprising outcome is nonetheless accompanied by an ex-ante probability. We assume that markets know and accept an anticipated individual market value γ_i for firm i, in the event that the Paris Agreement is a success. π_i denotes the market's ex ante probability assessment that the agreement is passed in the final, more ambitious wording. A firm's stock market reaction ΔV_j on the first trading day after the agreement happened (Monday 14 December) is then given

[14]In other words, inference based on CAARs reduces the likelihood of observing significant effects, even though a true difference exists. It increases the likelihood of observing no significant effects, even though a true significant difference exists. The comparison is with respect to firm-specific cumulative abnormal returns and average abnormal returns

[15]Using the Cowan (1992) adjustment for CAARs is important as these nonparametric tests were developed to examine single-day returns (Kolari and Pynnonen, 2011). The Cowan (1992) approach overcomes the potential problems with the Corrado test by cumulating daily ranks of abnormal returns within the CAR-period.

[16]In other words the test is robust to heteroskedasticity arising from unexplained variation in the true abnormal returns Harrington and Shrider (2007)

by:

$$\Delta V_i = (1 - \pi_i)\gamma_i \tag{8}$$

It represents the change in the market value for firm i in a scenario where the agreement is passed compared to the counterfactual of it not being passed. It captures the effect of the resolved uncertainty in the market following the agreement. As the probability of success is unknown prior to the agreement, the market's reaction to the agreement therefore understates the total impact on the firm value. Conceptually, this is similar to Kogan et al. (2017) who examine capital market responses to firms successfully being ranted patents, after a period of uncertainty between the patent filing and decision dates. With the Paris Agreement, we may expect a gradual onset of effects, slower than investors' responses to more common events such as earnings announcements. This is because the Paris Agreement contains a complex set of information that takes time to be understood and absorbed by the market, such as the ambition of countries' pledges.

4 Data

This paper brings together data from four sources to create a comprehensive panel of US listed firms with information on their financial and environmental activities. This section describes the sources and structure of the data. Descriptive statistics for each of the subsamples are reported in the Appendix in Table A.1.

Financial Data

Daily stock prices are obtained from The Center for Research in Security Prices (CRSP), which includes more than 32,000 securities with primary listings in any of the main US stock indices (NYSE, AMEX, or NASDAQ).[17] A credible and comprehensive counterfactual is needed for the validity of event studies. As the underlying "market" counterfactual, we use the excess market return factor ($R_m - R_f$) available from Kenneth French's website.[18] It captures the value-weighted return of the universe of all CRSP firms incorporated in the US (Fama and French, 2004; Kolari and Pynnonen, 2011). The data for the SMB and HML factors is obtained from the same source.[19] Daily stock price data of the individual firms in the respective portfolios are linked to the three factors by trading day.

[17] The data is downloaded through Thomson Reuters Datastream in March 2019.

[18] `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. (We downloaded the data on 18 March 2019).

[19] More recently data on the SMB and HML factors has also been provided for other parts of the world e.g. for Europe or a global coverage. However, these are constructed by using regions' value-weighted portfolios. Hence, different country-weightings in our available green revenue and emissions data would make the results less reliable and may introduce bias. For European and global portfolios we observed significant abnormal returns across many pre-negotiation periods, which indicates that the market may not be a suitable counterfactual for the selected portfolio of firms. This prevents robust causal analysis, as any significant abnormal returns in a post-event period may also simply result from using a poor counterfactual. Hence, we have focused on US firms in this analysis.

Green Revenue Data

To construct portfolios of "green" firms, and identify firms that have undertaken strategic shift towards low carbon markets, we use a novel dataset developed by the financial services company *FTSE Russell* which contains detailed information on listed firms' annual revenues attributable to "green" goods and services. To estimate each firm's contribution to the green economy, FTSE Russell (2010) first define the green economy using a "Green Revenues" classification model. This model contains ten broad green sectors and 60 green sub-sectors, and covers a wide range of activities related to the environment including both goods and services. The data includes sectors traditionally regarded as green, such as low carbon energy generation, energy efficiency equipment, and waste- and natural resource management, but also sectors that are more recently regarded as green, such as electric vehicles, renewable electricity, railways operation, smart cities design and -engineering. Thus it recognises that the green economy embraces many sectors in the economy and comprises a broad range of firms of different shades of green. Having defined the green sectors, FTSE analysts search through firms' annual reports for evidence of engagement in green subsectors. This analysis is conducted in a centralised way to reduce potential bias from self-reported non-quantifiable environmental performance metrics provided by the firms themselves.

For each firm and year, the aggregate of sub-sector green revenues is divided by total revenue to express a firm-year level green revenue share with values between 0 and 100. There are many cases where firms indicate that they are active in a green sub-sector but the exact revenue attributed to that activity is not disclosed. In these cases, the data provider reports a possible range of values – a minimum and maximum value – of the green revenues by sub-sector (for further details on the data see Kruse et al. (2020)). In our analysis we only use the minimum value of this range, which provides a conservative lower bound in the case of imprecise green revenue shares.[20]

Using this data, we calculate the green revenue shares by company, then construct deciles according to their green revenue share in the year 2013. This year was chosen so as to avoid anticipation effects. This measure is continuous, objective and covers many firms across a broad range of sectors, hence it has clear advantages over measures used previously to capture green-product development, either through surveys (e.g. González-Benito and González-Benito, 2005; Jabbour et al., 2015) or data on media announcements about new green product introductions (Palmer and Truong, 2017).

In our preferred specification we focus on the greenest deciles of firms. Specifically, we look at the top 3 deciles of green firms (N=63 firms, GR=97-100%).[21] We also look at firms generating one hundred percent of their revenue from green activities (N=51). As robustness checks and

[20] It can be argued that firms, which are actually generating green revenues, but are not included in our 'treated' dataset because they do not disclose their precise revenue share may violate the Stable Unit Treatment Value Assumption (SUTVA) assumption. In particular this may mean that the potential outcomes may not be well defined as some "treated" firms are not identified as such. However, this would work against our estimated coefficients. Hence, our results are conservative estimates.

[21] Due to equal values (taking the value of 1) it is not possible to analyse the top 10 or 20% separately. The smallest feasible cut-off is the top 30%.

to establish the intensive margin effects we also examine portfolios constructed as the top 40% (N=83, GR=70-100%), the median decile (N=22, GR=25-42%), and as the most conservative estimate, firms with any positive green revenue share between 2009-2013 (N=249). The entire dataset covers approximately 16,500 global publicly listed firms, representing approximately 98% of global market capitalisation for the years 2008-2017.[22] Our final sample includes approximately 5,000 US listed firms, of which 249 have at least some green revenue between 2009 and 2013. Firms that generate green revenues tend to be quite specialised in green activities, with the median firm generating more than 40% of their turnover from green goods and services. [23][24]

Emissions Intensity Data

To construct portfolios of "brown" firms, and identify firms that are likely to be impacted by the low carbon transition, we collect data on the emissions intensity from the *Trucost* Emissions dataset. It provides detailed emissions, and emissions-intensity information for firms representing approximately 93% of global market capitalisation.[25] We use Scope 1 and Scope 2 emissions for our analysis. Scope 1 emissions are direct emissions from owned or controlled sources (typically power plants). Scope 2 emissions are emissions from purchased electricity, heat or steam. Scope 3 emissions are indirect emissions not captured by Scope 2 such as transport related activities in vehicles not owned or controlled by the entity, waste disposal or outsourced activities. Scope 3 emissions are notoriously difficult to measure and we are concerned about the data quality, which is why we omit them from the analysis. Emissions-intensity (EI) is defined as emissions (tons) of carbon dioxide equivalents (CO_2e) divided by revenue in million US dollars. We treat scope 1 and 2 as two separate subsamples, but also group them together as a separate subsample. For the latter we simply construct a portfolio of the most emissions intensive firms according to their sum of scope 1 and 2 emissions. To categorise firms into emissions-intensity deciles, we use firms' average carbon intensity for the period between 2009-13 to smooth potential outliers.[26]

Patent Data

In addition we also use clean patents as a measure of "green" firms. The patent data is provided by the World Patent Statistical Database (PATSTAT) which is maintained by the European Patent Office (EPO)[27]. The low-carbon patent classification (Y02) recently developed by the European Patent Office (EPO) allows us to identify low carbon technologies and attribute them

[22] We omit the earliest year 2008 due to concerns about data quality for that year similar to Kruse et al. (2020).

[23] Across the entire sample of more than 5000 firms, the average firm generates 2-3% of green revenues according to our minimum green revenue indicator.

[24] It is important to note that non-listed firms and smaller listed companies are not covered by FTSE Russell, hence our analysis provides a lower-bound of the true size.

[25] For the time period up to 2013, which we use in our empirical analysis, the Trucost data represents approximately 85% of global market capitalisation.

[26] Again, we use the top deciles of the most emissions intensive firms to construct our portfolios of emissions intensive firms (Scope 1: (N=102) mean (median) EI= 2601 (1468) (tCO_2e/USDm); Scope 2: (N=103), mean (median) EI = 170 (125) (tCO_2e/USDm); Scope 1&2: (N=101) mean (median) EI=1356 (909) (tCO_2e/USDm)).

[27] For a detailed account of the data see Dechezleprêtre et al. (2017)

to firms. [28] We construct a measure of clean patent intensity by taking the share of granted Y02-patents between 2000-13 and divide it by the total number of patents granted over the same period.[29] This measure captures the extent to which firms are patenting in clean technologies compared to their overall level of patenting. As previously, we examine the top decile (N=37) of firms with the highest clean patent intensity.[30] Patent applications offers a measure of the level of attention a firm pays to environment. Specifically, studies have looked at the share of "green" or "clean" patents relative to total patents, to capture firms' strategic shift towards low carbon markets (Lanjouw and Mody, 1996; Jaffe and Palmer, 1997; Veugelers, 2012; Dechezleprêtre et al., 2017). However, there are few clean patents and sample size is small when using this measure, hence we use this as a robustness test. While patent counts and their citations offer a relatively homogeneous measure of technological novelty and are available for long time series, they also have well known drawbacks as indicators of firm innovation activity. Not all innovations are patented, different technologies are differently patentable, and the propensity to patent innovations varies considerably across types of firms, sectors and countries (Malerba and Orsenigo, 1995). Granted patents capture only successful innovations, therefore representing only a fraction of innovation activity (Lychagin et al., 2016). Moreover, they mainly capture inventions and do not capture the diffusion or adoption of new technologies. Finally, given that some sectors rely more on patents than others, using patent data may lead to a biased view of the green economy.

5 Results

We present our results in figures showing the event path over three time windows: (1) the ten days (2-trading weeks) prior to the beginning of the negotiations of the Paris Agreement (pre-negotiation period), (2) the ten day negotiation period, and (3) the ten days following the agreement (post-negotiation period). All our results are reported using the nonparametric Corrado (1989) rank test with the aggregation approach by Cowan (1992) for cumulative average abnormal returns (CAARs).

5.1 Abnormal returns of green firms

We first focus on the greenest firms (i.e. the top 30% of green firms). These firms have a green revenue share of between 97-100%. Figure 2 presents 3-day 'rolling' cumulative average abnormal returns (CAARs). There is an increase of 6% in the returns around the respective median day for these green firms in the days following the agreement. We observe a gradual

[28] Unfortunately, there is no good equivalent to the clean YO2 classification for dirty patents. We are therefore unable to focus on brown patents.

[29] We allow for a slightly larger time period compared to the green revenue and emissions intensity data since patents might require some time to be reflected in firms' products, production processes or other tangible outputs. Also, many firms do not file a (clean) patent each year which prevents us from using a single year to define the quantiles.

[30] This sample of firms with the highest clean patent intensity has an average share of clean to total patents granted of 0.67. Hence, on average more than half of their granted patents are green.

onset of the effects that persist for approximately five days following the agreement. This is in line with findings showing that large and complex amounts of information may overwhelm investors and slow their reactions to a particular event because of limited cognitive attention (Hirshleifer et al., 2009).[31] [32]

Importantly, the portfolios of firms are not systematically different from the market in the pre-negotiation window. The vertical bars show confidence intervals. The presence of the heads of state during the first days of the negotiation contributed to early optimism that the agreement could be passed. This early optimism shifted towards uncertainty in the last three trading days prior to passing of the agreement (Dec 12). Negotiations extended beyond the official deadline (Dec 11) which increased uncertainty. The first trading day after the agreement (Monday 14 December 2015) is our first post-treatment day (day 0 in the event analysis), because stock markets are closed over the weekend.[33] We observe that the abnormal returns prior to the passing of the agreement are not significantly different from zero. In the first days following the agreement, the uncertainty around the returns is diminished and the confidence intervals become much narrower. After the first week following the agreement, the abnormal returns gradually level off, and are no longer significantly different from zero in the second week following the agreement. By this point, new information had been priced into the market.

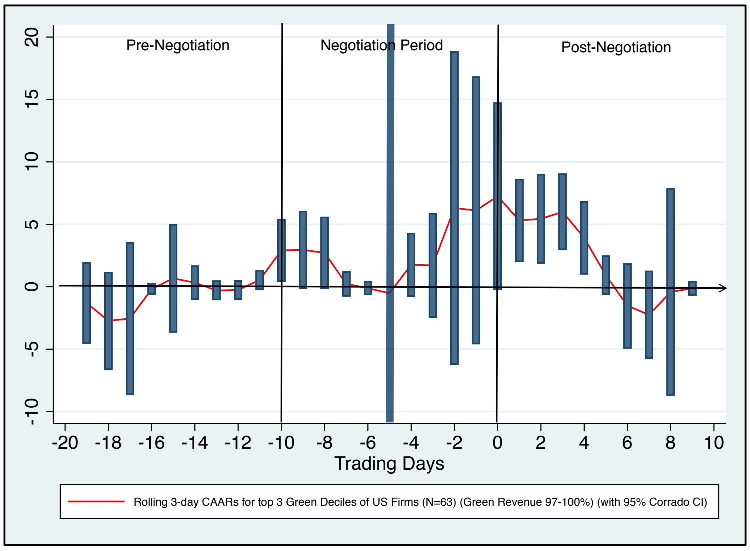


Figure 2: Event Path for top 30% green firms (top 3 deciles)

[31] Hirshleifer et al. (2009) show that on days when a large number of announcements are made by different firms investors tend to under-react to individual firms' earnings announcements. Hence investors can also be overwhelmed by a large amount of standardised events.

[32] Investors' responses to the Paris Agreement may be systematically different from their response to more common events such as earnings announcements, which occur frequently and in a standardised format. Investors had to absorb a large amount of information that was contained in the agreement. Moreover, the relative stringency of the agreement had to be understood by assessing the level of ambition of individual Nationally Determined Contributions (NDCs). Since the agreement relies on voluntary emission reductions, the political interpretation in the days following the agreement became important. Absorbing such a complex set of information might therefore be different from reacting to more common and standardised stock market events such as earnings announcements (e.g. MacKinlay, 1997).

[33] Stock markets open from Monday to Friday, and are closed during the weekend. The NYSE opens for instance at 9:30am and closes at 4pm Eastern Time, Monday to Friday. Early-hours trading exists, where traders can enter trades before the official opening. These orders are then queued before the opening. Furthermore "after-hours" trading exists, which is a niche field of stock trading where trading volumes are low. The NYSE after-hours trading is open Monday to Friday 4pm to 8pm Eastern Time, but is also closed on weekends

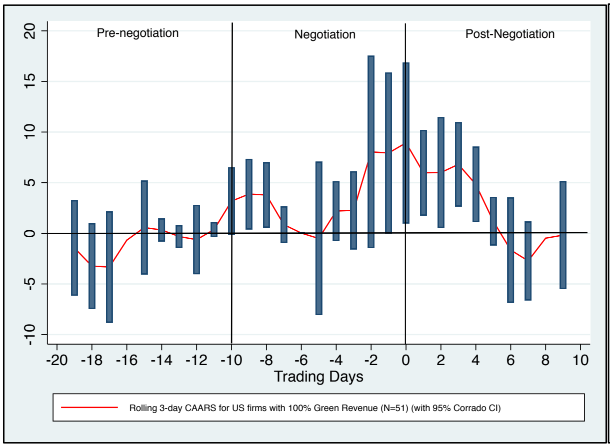
Note: This figure shows the event path using rolling 3-day CAARs of the top 30% of green firms (top 3 deciles). The red line shows the rolling 3-day CAARs. The blue bars show the 95% Corrado-Cowan confidence intervals. Monday 14 December 2015 is event day 0. The estimation window is the 100 days prior to the pre-negotiation period.

To further examine the intensive margin, we examine different definitions of green firms in Figure 3. We first take the extreme definition where green firms are those that have one hundred percent green revenue share (N=51) (Figure 3a). The result is similar is magnitude with CAARs of 6-7%. As a second step, we then look at the top 40% of green firms (N=83) (Figure 3b) and observe significant CAARs between 4-5%. For these portfolios of firms, we observe very similar trends as for our main specification. We observe that the variance in returns increases substantially prior to the event, as seen by the large confidence intervals. The confidence intervals become small following the event as the uncertainty is resolved. Thirdly, we look at the median (5th decile) of green firms (with a green revenue value between 25-42%) (Figure 3c). Since this portfolio includes firms from only one decile of green firms (the median decile), the sample size is smaller (N=22) than in the other portfolios. This can make the statistical inference more difficult. However, even for this relatively small portfolio of firms the effects remain significant at the 5% level. We observe CAARs of between 2-3%. Finally, we also examine firms which have generated at least some positive green revenue share (> 0%) between 2009-13 (N=249)(Figure 3d). This sample consists of relatively heterogeneous firms, including purely green ones, as well as firms that produce only marginal green revenue shares. Hence, we would expect the effects to be less clear-cut and smaller in magnitude compared to the main specification. In line with these expectations, we observe significant CAARs of between 2-3%.

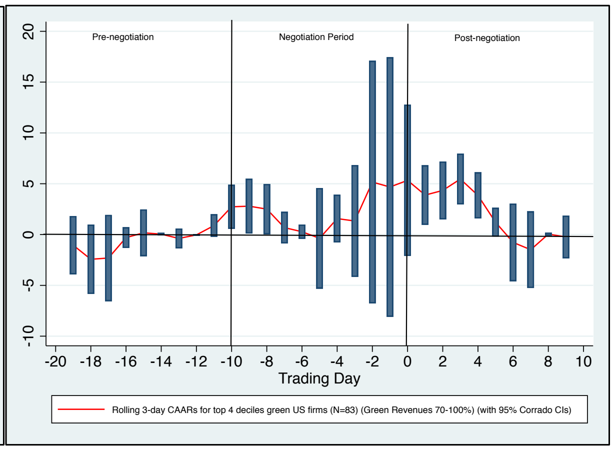
Across all models we observe that using the BMP test statistics instead of the Corrado test tends to result in smaller standard errors and more pronounced significance of effects (see Figure H.1 in the Appendix). Using the KP statistic instead, we observe that the standard errors increase relative to the main specification. We still observe significant effects (at 5%) across the different portfolios (see Figure I.1 in the Appendix). Thus, overall we observe a clear effect, showing that green firms have significantly outperformed the market in the week following the Paris Agreement.

In Table 1 we test whether the returns are significantly different from another. In particular we compare the returns of the two greenest samples (portfolio of firms in the top 3 deciles, and firms with a 100% green revenue share) to the firms in the top 40%, to the median decile, and the conservative group of firms with any green revenue share. Across all six combinations we observe highly significant differences with the greenest firms experiencing significantly higher abnormal returns than the other three groups. Our results therefore point to intensive and extensive margin effects. Firms with high green revenue shares have outperformed both the overall market and firms with lower green revenue shares.

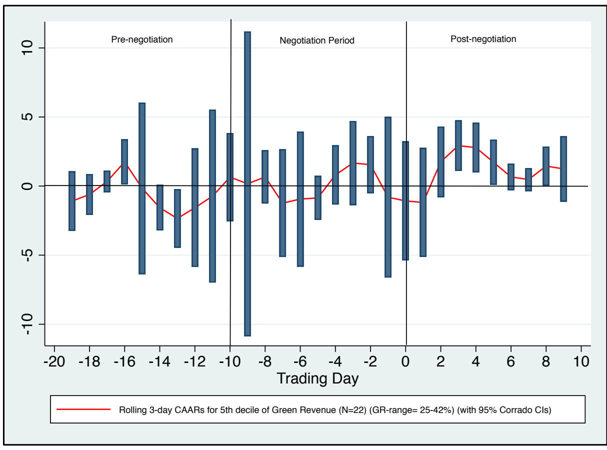
To assess the magnitude of the effect, we use the (non-rolling) cumulative average abnormal returns over the entire post event window [0,5] (in line with Oberndorfer et al., 2013). From the previous results we have seen that the effect persists for about five days following the agreement.



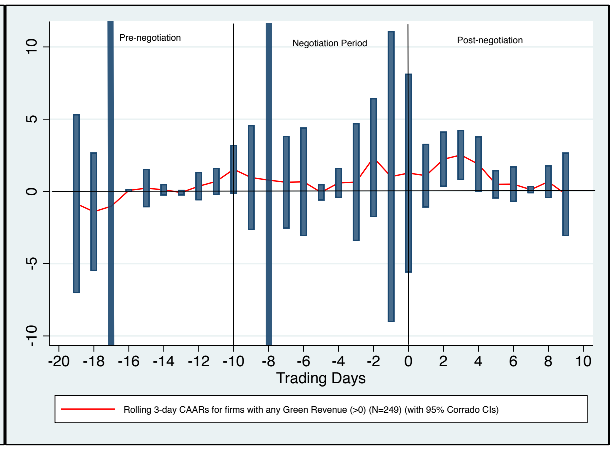
(a) Event Path for firms with 100% Green Revenue in 2013)



(b) Top 40% green firms (top 4 deciles)



(c) Median (5th) decile of green firms



(d) Any green revenue (>0) between 2009-13

Figure 3: Event Paths for portfolios consisting of firms with different green revenue intensity (intensive margin)

Note: This figure shows the event path using rolling 3-day CAARs. Panel (a) shows the CAARs of firms with 100% Green Revenue. Panel (b), shows the CAARs of the top 40% of green firms. Panel (c) shows the CAARs of the median decile of green firms. Panel (d) shows the CAARs for firms with any positive green revenue between 2009-13. The red line shows the rolling 3-day CAARs. The blue bars show the 95% Corrado-Cowan confidence intervals. Monday 14 December 2015 is event day 0. The estimation window is the 100 days prior to the pre-negotiation period.

Sample (a)	Mean (Std. Dev.) (CAAR [0;5]	Difference tested with respect to sample (b)	Mean (CAAR [0;5])	Two-sided t-test and (p-value)	One-sided t-test Sample(a) > Mean(b)
Sample with Green Revenue =100%	10.81 (2.34)	Any Green Revenue (>0)	2.98	3.34 *** (0.0016)	(0.008)***
	10.81 (2.34)	Deciles 5-7 of most Green firms (Green Revenue range (25-96%)	3.83	2.98 *** (0.004)	(0.002)***
	10.81 (2.34)	5th Decile (GR-range: 25-42%	1.60	3.93*** (0.0003)	(0.0001)***
Sample Top 30% green (deciles 8-10) (GR-range 97-100%)	9.22 (1.96)	Any Green Revenue (>0)	2.98	3.19*** (0.002)	(0.001)***
	9.22 (1.96)	Deciles 5-7 of most Green firms (Green Revenue range (25-96%)	3.83	2.75 *** (0.008)	(0.004)***
	9.22 (1.96)	5th Decile (GR-range: 25-42%	1.60	3.93*** (0.0003)	(0.0001)***

Table 1: T-test to test difference in intensive GR-margin for CAAR [0;5]

Note: This table shows the t-test results (one-sided and two-sided) to compare the post-event CAARs (days 0-5) across the different portfolios. The mean and standard deviation of the CAARs for the greenest samples are reported in column 2. The mean CAARs of the firms in the relatively less green portfolios are reported in column 4. Column 5 reports the results from the two sided t-test, and column 6 reports the results of the one-sided t-test.

Therefore, we use this window size to quantify the entire magnitude of the effect.[34] In this entire post-event window following the Paris Agreement the greenest firms (top 3 deciles and firms with 100% GR) experienced nearly 10% significantly (at 5%) higher returns (Figures G.1a and G.1b). For the conservative sample of 249 firms with any green revenue, we still observe significantly (at 5%) higher average returns of nearly 3% over this entire post-event window G.1e. The effect is also significant for the top 40% of green firms, which observe 8% higher returns. For the median decile of green firms the effect is only marginally significant, showing nearly 2% higher returns. The decline in significance may arise because of the relatively small sample size of the median decile (N=22) and the wider averaging compared to the main results.[35]

The effects imply that on average the market capitalisation[36] of the firms in the 3 greenest deciles increased by 10% following the Paris Agreement relative to the overall market. On average these firms have a market capitalisation of 2 billion USD (Table A.1). Hence, the

[34]Using this wider window also provides a more conservative robustness check in terms of significance of the coefficients. If for instance the true effect for a particular sub-sample only exists for the first two days, then the likelihood of a type 2 error increases, as we average over a wider time window. The type 2 error captures the likelihood of failing to reject a false null hypothesis (of no difference).

[35]The effect is also significant (at 5%) for the sub-sample of the top 3 deciles excluding electricity generation with 7% higher returns G.1f, which is discussed in more detail in the section 5.3.2.

[36]Market capitalisation is measured as (share price × number of outstanding shares)

market capitalisation of the greenest firms increased on average by approximately 200 million USD following the Paris Agreement and compared to the overall market. This is equivalent to a relative increase in market capitalisation of approximately 12.6 billion USD across these firms. The larger sample of 249 firms with any positive green revenue share has an average market capitalisation of 6 billion USD. With a 3% higher return over the entire post-treatment period, the market capitalisation of such firms increased by approximately 180 million USD, compared to before the agreement, and relative to the overall market. Over the 249 firms this is equivalent to an increase in market capitalisation of approximately 45 billion USD compared to the overall market.[37] These effects are both statistically significant and economically meaningful.

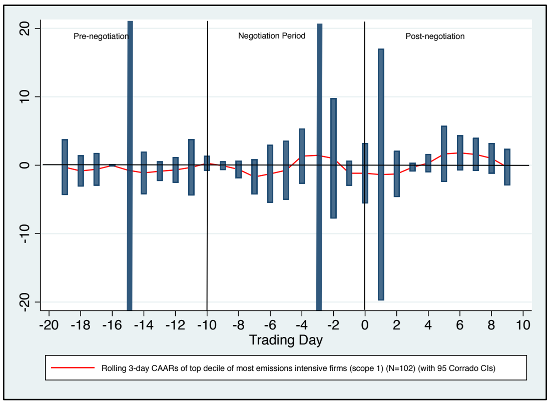
5.2 Abnormal returns of emissions-intensive firms

Next, we move on to the question as to whether investors' valuations of pollution intensive firms respond to a positive environmental event, in this case the Paris Agreement, building on the existing literature (e.g. King and Lenox, 2001; Konar and Cohen, 2001; Matsumura et al., 2014) which tends to find that markets punish firms in response to unfavourable environmental performance. With growing ambition on climate change mitigation emissions-intensive firms might experience declining market shares or even stranding of their assets. This might apply to both their physical assets such as fossil reserves as well as intangible assets such as knowledge stocks. However, we have also observed political measures to compensate emissions-intensive firms (e.g. Germany during the coal phase-out (e.g. Sen and von Schickfus, 2019)). Abnormal negative returns for the most emissions-intensive firms can provide insight into investors' perception of the global commitment, and their willingness to divest from emissions-intensive economic activities.

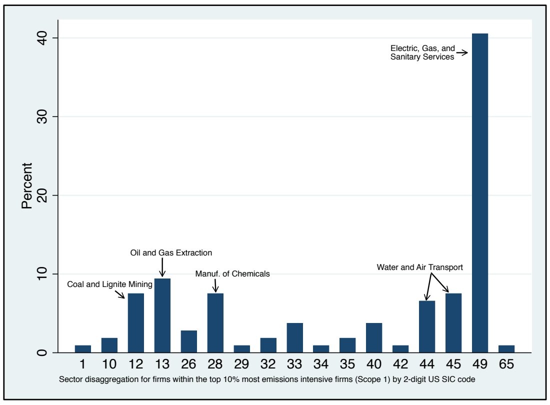
Figure 4 presents the abnormal returns for emissions-intensive firms according to the emissions of scope 1, scope 2 and both of them together. In all three cases, we do not observe significant abnormal returns following the agreement. Interestingly the agreement seems to have introduced a substantial degree of variability in returns for highly emissions intensive firms, as seen by the large increase in the confidence intervals around the event date (Figures 4a, 4c, and 4e). This suggests that some firms might have experienced highly positive returns, while others suffered negative returns. We disentangle the effect by examining sector-specific returns. The distribution of firms across sectors is different for scope 1 and scope 2 emissions. Scope 1 is heavily dominated by electric, gas, and sanitary services, whereas Scope 2 shows a more diverse spread across sectors (Figure 4b and 4d). In particular we disaggregate the effect for scope 1 emissions by the largest sectors. We do not observe any significant sector-specific effects for scope 2 emissions, which are therefore omitted from the results.[38]

[37]For comparison, the overall market capitalisation of all domestic US companies was approximately 25 trillion USD over the same time period. The increase of 45 billion USD is therefore roughly equivalent to a 0.2% increase of the overall US market capitalisation (The World Bank, 2019). It is important to note that this provides a back-of-the-envelope calculation and denotes the relative increase in market capitalisation compared to the overall market.

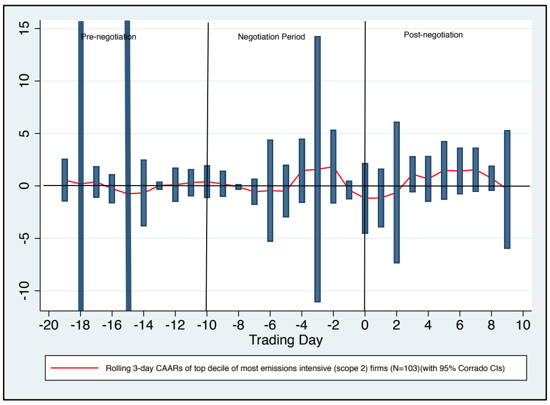
[38]It might be difficult for investors to assess the effect on firms that are highly reliant on electricity. However, it might also be the case that these firms will become automatically less carbon intensive, as the overall electricity grid shifts to renewables. It could be argued that firms, which purchase electricity from the grid might only be affected if the electricity price changes substantially as a result of a shift to renewables. Yet, the sharp decline



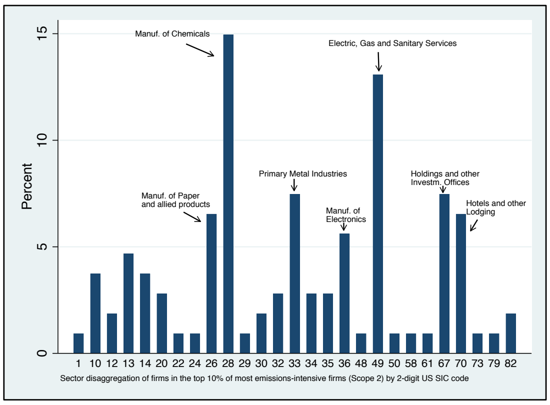
(a) Event Path Scope 1



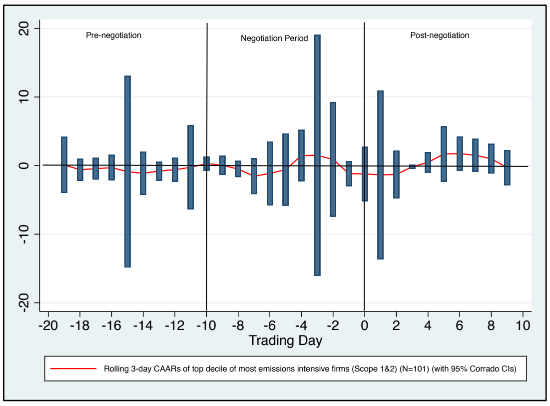
(b) Sector composition Scope 1



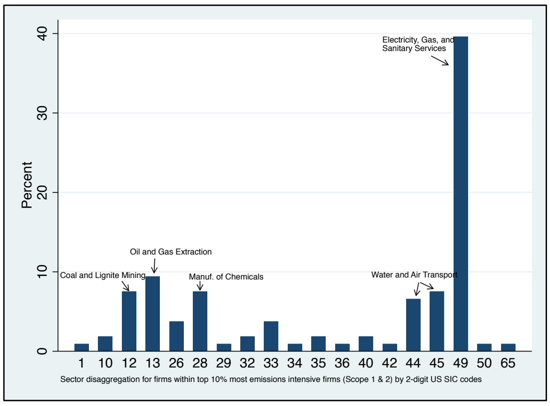
(c) Event Path Scope 2



(d) Sector composition Scope 2



(e) Event Path Scope 1 & 2



(f) Sector composition Scope 1 & 2

Note: This figure shows the event path using rolling 3-day CAARs in Panels (a), (c), and (e) and the sectoral composition of the firms in the respective portfolios in Panels (b), (d), and (f). The red line shows the rolling 3-day CAARs. The blue bars in the figures in the left column show the 95% Corrado-Cowan confidence intervals. Monday 14 December 2015 is event day 0. The estimation window is the 100 days prior to the pre-negotiation period. Firms are divided by 2-digit US SIC codes. The codes cover: (1) Agricultural Products - Crops, (10) Metal Mining, (12)Bituminous Coal and Lignite Mining, (13) Oil and Gas Extraction, (14) Mining and Quarrying of Nonmet. Minerals, (20) Food and Kindred Products, (22) Textile Mill Products, (24) Lumber and Wood Products, (26) Paper and Allied Products, (28) Chemicals and Allied Products, (29) Petroleum Refining , (30) Rubber and Misc. Plastic Products, (32) Stone, clay, glass, concrete products, (33) Primary Metal Industry, (34) Fabricated Metal Products, (35) Indust. and Commercial Machinery, (36) Electronic and other Elect. Equipm., (40) Railroad Transport, (42) Motor Freight Transp. and Warehousing, (44) Water Transp., (45) Transp. by Air, (48) Communications, (49) Electric, Gas, Sanitary Services, (50) Wholesale Trade - durable goods, (58) Eating and Drinking Places, (61) Non-depos. credit inst., (65) Real Estate, (67) Holding and other Invest. Offices, (70) Hotels and other Lodging, (73) Business Services, (79) Amusement and Recreation Services, (82) Educational Services

Figure 4: Abnormal returns of 10% most emissions intensive firms (Panel (a), (c) & (e) and the respective sectoral distribution (Panel (b), (d) & (f))

We begin by isolating the effect of electricity generating firms (the largest sector) where we observe small positive and marginally significant effects (Figure 5a). On the contrary, the effect for the most emissions-intensive firms in oil and gas extraction (the second largest sector) is negative and marginally significant (Figure 5b). When excluding all public utilities (Electric, Gas, and Sanitary Services), the effect is negative and marginally significant (Figure 5c). Hence, electricity generating firms and public utilities appear to play a special role and behave significantly different to other emissions-intensive firms. Again, we observe smaller standard errors when using the BMP test statistic so that the effects for the sector-specific sub-samples become significant at 5% (Figure H.2 in the Appendix).

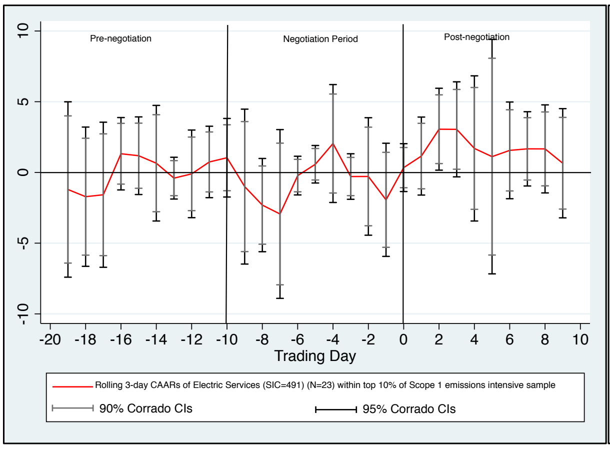
Using the *FTSE Russell* Green Revenue database, we further investigate the electricity generating firms that are among the most emissions intensive firms, but experience positive abnormal returns after the Paris Agreement. We observe that all of these firms, even though they are highly emissions intensive, are also engaged in green technologies, largely in renewable electricity generations. Many firms even have substantial revenue shares from renewable energy generation. The subsample of the most emissions-intensive (scope 1) firms has a mean of 7% and maximum of 35% in the conservative minimum green revenue variable. All of the firms in this subsample are active in at least one green subsegment as defined by *FTSE Russell*.[39] This finding suggests that for electricity generating firms with mixed portfolios of highly carbon intensive fuels as well as renewable shares, the latter appears to be particularly valued by investors. Investors might anticipate that it could be easier for electricity generating firms to shift from carbon-intensive to renewable electricity generation compared to other sectors in the economy.

5.3 Robustness Checks

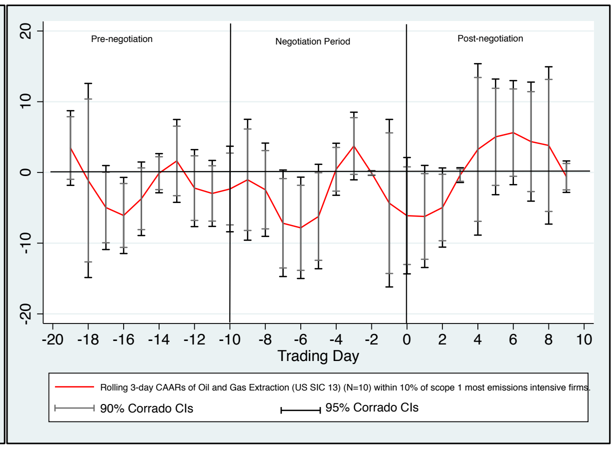
For all our results, we use the (Boehmer et al., 1991) BMP and (Kolari and Pynnonen, 2010) KP parametric test statistics as robustness checks on the statistical inference (See Figures H.1 and H.2 in Appendix H for results with BMP tests and Figures I.1 and I.2 in Appendix I for results with KP tests). As discussed above, we also report the CAARs for the entire post event window (days 0-5) in Figures G.1 and G.2 in Appendix G. Using the wider event windows provides also a conservative robustness check in terms of the significance of the results. If for instance the true effect for a particular sub-sample only exists for the first two days, then the likelihood of a type 2 error increases as we average over a wider time window. In other words it may increase the likelihood of failing to reject a false null hypothesis (of no difference). Furthermore, we also report the average abnormal returns (AARs) in Figures J.1 and J.2 in Appendix J.

in the costs of renewables that have in parts already made them competitive with fossil fuel electricity might mitigate such concerns for investors.

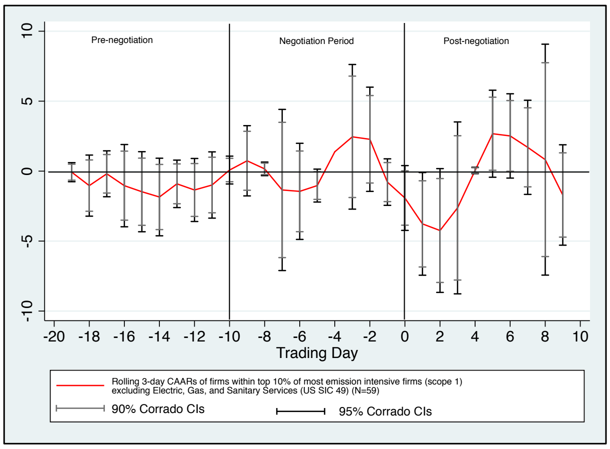
[39]Firms in this subsample might have a minimum green revenue share of 0 due to incomplete reporting of the precise revenue share from a particular green subsegment. Yet, for all firms in this subsample the analysts have identified a green subsegment, in which the firm is active.



(a) Electric Services



(b) Oil and Gas Extraction



(c) Excluding Electric, Gas, and Sanitary Services

Figure 5: Event Paths for specific sectors (among the 10% most emissions intensive firms (Scope 1))

Note: This figure shows the event paths using rolling 3-day CAARs. It disaggregates the paths by sector for the most emissions-intensive firms (scope 1). Panel (a) shows the CAARs of the most emissions intensive firms within Electric Services (SIC=491; N=23). Panel (b) shows the CAARs of the most emissions intensive firms within Oil and Gas Extraction (SIC=13; N=10). Panel (c) shows the results for the most emission-intensive firms excluding Electric, Gas and Sanitary Services (Excluding SIC 49; N=59). The red line shows the rolling 3-day CAARs. The black bars show the 95% Corrado-Cowan confidence intervals. The grey bars show the 90% Corrado-Cowan confidence intervals. Monday 14 December 2015 is event day 0. The estimation window is the 100 days prior to the pre-negotiation period.

5.3.1 Abnormal returns of firms patenting in clean technologies

We might be concerned that unobservable particularities of the green revenue share data might be driving our results. We complement our results using clean patents as a measure of green firms. Even though green revenues and clean patents capture different stages of firms' innovation in green technologies, we would expect the same sign on the effect for firms with a high intensity of clean patents. Only three firms are included in our sample of the top green firms and the top clean patenting firms. Hence, any similar effect is not just an artefact of capturing the same firms. Figure 6 shows that a significant positive effect exists with CAARs of around 2-3% for the top decile of clean patenting firms. This confirms our previous results.

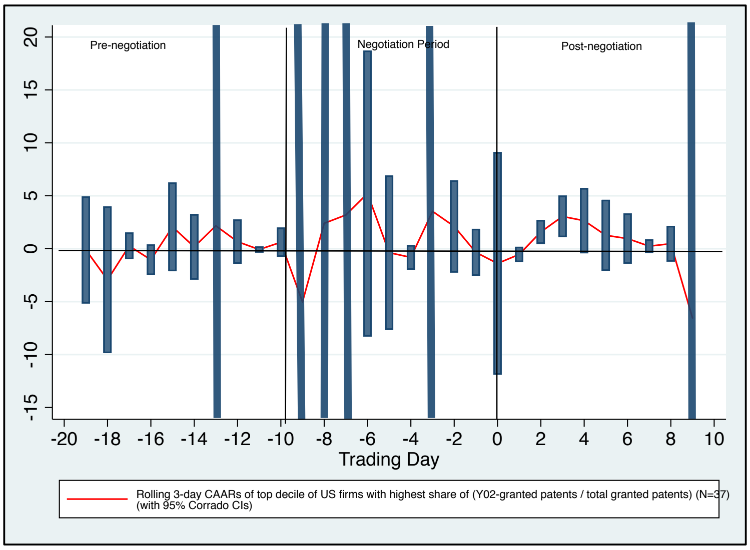


Figure 6: Abnormal Returns of top decile of firms with the highest clean patent intensity.

Note: This figure shows the event paths using rolling 3-day CAARs for the top decile of firms with the highest clean patent intensity. The red line shows the rolling 3-day CAARs. The blue bars show the 95% Corrado-Cowan confidence intervals. Monday 14 December 2015 is event day 0. The estimation window is the 100 days prior to the pre-negotiation period.

5.3.2 Excluding Electricity Generation

As a further robustness check we exclude electricity generating firms from the analysis. We are concerned that the effects might be driven by renewable energy generation which may be a unique sector due to sector-specific subsidies and other support measures. Electricity generating firms (US SIC 491) also form the largest group of approximately 18% in our sample (see Figure C.1).[40] Figure 7 shows that the effect persists when excluding electricity generation and shows significant abnormal returns of around 4-5%.[41] The results are still also marginally significant when excluding all public utilities Electricity, Gas, and Sanitary Services (SIC 49), which however reduces the sample size substantially (see Figure D.1 in the Appendix).

[40] The sector distribution at the 2-digit SIC code level is shown in Figure B.1

[41] We report all robustness-checks, which cover only certain sectors with both 90% and 95% confidence intervals. This allows us to also report marginal significance in particular when the portfolio size becomes small.

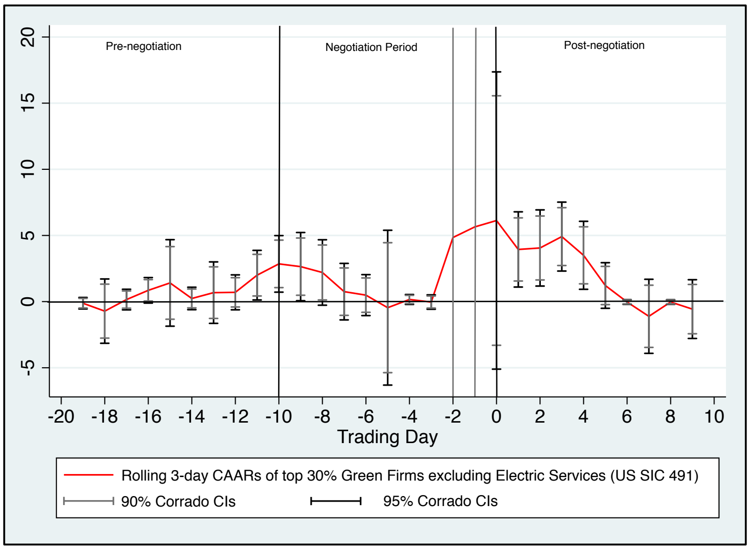


Figure 7: Event Path of top 30% green firms excluding Electricity Generation

Note: This figure shows the event paths using rolling 3-day CAARs for the top 30% of green firms, excluding firms in Electricity Generation (Excluding SIC 491). The red line shows the rolling 3-day CAARs. The black bars show the 95% Corrado-Cowan confidence intervals. The grey bars show the 90% Corrado-Cowan confidence intervals. Monday 14 December 2015 is event day 0. The estimation window is the 100 days prior to the pre-negotiation period.

5.4 Evidence in Support of Event Study Assumptions

The Paris Agreement was a major event that did not go unnoticed. Information on the negotiation progress was regularly released. This is mirrored in the event path, as we observe an increase in the volatility during the negotiation window and in particular in the last days prior to the passing of the agreement. To show that the event was of importance and did not go unnoticed, we use Google Trends that provides a measure of the relative frequency of searches for a specific keyword by week and region. It shows that the spike in searches for the term "Paris Agreement" occurred in the US in the week 13. - 19. December 2015, i.e. just after it was passed (See Figure F.1 in the Appendix). The Google Trend statistics show spikes on dates, for which we would expect increased searches for the term. We would be concerned if the line was flat or showed no spike during the event study period.

A fundamental condition for event studies is the element of surprise. If the event was perfectly anticipated we would not expect to see any abnormal returns as the event would already be priced into the market. To establish that the Paris Agreement in its final form was unexpected, we make use of data on future contracts from the S&P 500 and the S&P 500 Energy Futures. It is possible that the Paris Agreement introduced overall uncertainty in the market leading to an increased demand for hedging through futures. If the final agreement came as a surprise, this would result in increased trading activity. We observe a substantial increase in the trading volume of the S&P 500 Futures (Figure 8) and the S&P 500 Energy Futures (Figure E.1 in the Appendix) on and around Monday 14 December 2015. Reassuringly, these figures suggest that the final agreement surprised market participants.

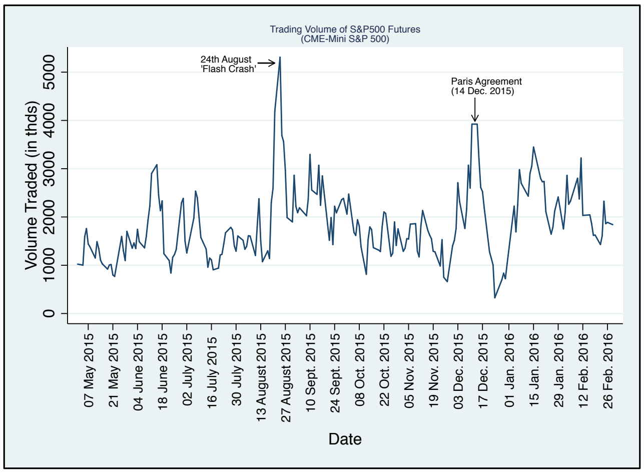


Figure 8: S&P 500 Futures Trading Volume

Note: This figure shows the trading volume (in thousands) of S&P500 Futures (CME-Mini S&P500) for a 10 month period between May 2015 and February 2016 including the passing of the Paris Agreeement.

For event studies to be reliable, it is important that there be no other confounding events that might drive our results. Of particular concern are events that affect green or emissions-intensive firms differently from the overall market. We apply a news search using the Factiva database to investigate if other events happened in the week following the agreement. We look in particular for events or policy announcements that would be beneficial to low-carbon technologies or impact emissions-intensive firms. We search for events using the keywords "climate", "renewables", or "emissions". Similar to Mukanjari and Sterner (2018) we find no significant events in the week following the agreement that would affect our results.[42]

To further dispel concerns of other confounding policies or announcements, we screen the most important general political and business news events in the week following the agreement. In particular, we want to mention two such events. First, in a widely expected move, the US Federal Reserve increased its interest rate by 0.25 percentage points on 16 December 2015. While this may be regarded as a positive signal, indicating that the US economy was growing stronger, it also increased the cost of borrowing for firms and households (Applebaum (2015), NYT). This event was widely anticipated and therefore already accounted for in stock prices. It also affected the entire market and hence is controlled for in our identification strategy, assuming that it had no differential effect across firms. Second, on the night from 15th to 16th December, the US Congress reached a deal to prevent a year-end government shutdown (Snell and DeBonis (2015) (The Washington Post)). This deal was reached as a compromise between the Obama White House and the Republican-controlled Congress. The deal included a $1.1 trillion USD appropriations package that would fund the federal government for the remainder of the 2016 fiscal year. It also included a tax break package, costing approximately $650 billion USD covering a large range of about 50 different credits for businesses and individuals. In addition, the bill also lifted a ban on crude oil exports. The effect of lifting the ban would, if anything, work in the

[42] Mukanjari and Sterner (2018) state that on 16 December 2015, news articles on record highs of global temperature as well on solar energy were published. They conclude however that none of the news coverage on these topics was of a sufficient magnitude or direct importance. We come to the same conclusion from our key word search.

opposite direction from what we observe for emissions-intensive firms in oil and gas extraction. The deal also included an extension of tax breaks for wind and solar energy producers for five years. The extension of the tax breaks for solar and wind industry could potentially inflate our results. However, these specific deductions were a relatively small part of the overall deal, which included among others state- and local sales tax deductions for businesses, which would have effected the overall market. The industry-specific extensions in tax breaks covered only a small set of renewable energy industries. Since our results also hold when excluding electricity generating firms, we are not concerned that this deal is driving our results.

A last concern is that the abnormal returns might have occurred simply due to increased media attention, which may have encouraged individuals to purchase "green" stocks. The effect might then not reflect a new "informed" perception of the post-Paris policy framework. However, it is important to remember that in the US the vast majority of stocks is owned by large scale investors rather than individuals. The latest available data from 2010 shows that 67% of all common shares were owned by large institutional investors (Gompers and Metrick, 2001; Blume and Keim, 2012) and has been increasing continuously since the 1950s[43]. This limits the ability for (potentially uninformed) individuals who purchase shares because of the increased media coverage to drive the substantial trends we observe across a number of relatively large portfolios.

6 Discussion

This paper examines whether global capital markets are responding to the low carbon objective. We show that investors do back companies that are leading the market in developing and adopting low carbon technologies, but they do not divest away from brown firms that are emissions-intensive and potentially slow in managing climate related risks.

Specifically, we show that "green" firms that generate a share of their revenue from producing green goods and services have significantly outperformed the market in the week following the Paris Agreement. The results are both statistically significant and economically meaningful. We identify a level shift in green firms' market capitalisation following the agreement. The sample of the greenest firms observed on average 10% higher returns for the entire post-event period (days 0-5) compared to the overall market. This is roughly equivalent to a relative increase of approximately 200 million USD in market capitalisation per firm, or a total relative increase of 12.6 billion USD in market capitalisation across the 63 greenest firms. The aggregate effect is even larger for the sample firms with a positive green revenue share. They exhibit an increase in market capitalisation of approximately 45 billion USD relative to the overall market following the Paris Agreement. In addition to this extensive margin, our results also reveal that the market values green firms at the intensive margin. Firms with high green revenue shares have significantly outperformed not only the overall market, but also firms with lower green revenue shares. Furthermore, we show that the overall results are not limited to electricity generation,

[43] Large institutional investors are defined as such when having more than 100 million USD under management.

the largest sector and subject to energy-specific subsidies. Investors seem to evaluate the post-Paris policy landscape as opening up further potential for firms producing green goods and services, and for the diffusion and adoption of green technologies.

We also show that on aggregate, the "brown" firms have not experienced significant abnormal returns following the agreement. This suggests that policy signals on climate change today are insufficient to bring rapid shift away from investing in fossil fuels towards low carbon. However, we observe negative (marginally significant) abnormal returns for oil and gas extracting firms and for all sectors excluding utilities. Such negative returns may reflect the anticipated challenges for firms in these sectors to adjust their business model to the post-Paris policy landscape. It could also reflect an increasing risk of 'asset stranding', as firms' carbon-intensive physical or intellectual assets become less valuable. Interestingly, the most emissions-intensive electricity generating firms seem to be valued differently. They have experienced positive (marginally significant) abnormal returns following the agreement. Merging the green revenue and emissions-intensity databases we are able to see that all of the most-emissions intensive electricity generating firms are also active in 'green' sectors, with on average 7% (and a range up to a maximum of 35%) of their revenue being generated from such activities, mostly from renewable electricity generation. For such partially green and brown firms, investors may face trade-offs regarding the relative valuation of the two components. The positive abnormal returns might suggest that investors anticipate the transition to low-carbon technologies to be easier for electricity generating firms relative to the overall market, and in particular relative to oil and gas firms.

The positive abnormal returns for green firms suggest that the post-Paris policy landscape may be able to open up growing opportunities for green goods and services. This may allow for some optimism with respect to the increasing diffusion and adoption of low-carbon and green technologies. The non-existence of significantly negative results for the overall sample of emissions-intensive firms is however a more cautionary finding. Given the drastic emission cuts that are required to limit global warming to well below 2°C, the results reinforce the urgency and importance of aligning financial markets with global action on climate change. Additional national and international efforts are likely to be needed. In particular, stringent carbon prices across sectors and countries appear to be necessary to establish clear incentives for financial markets to respond to decarbonisation- and low carbon objectives. Such price signals would lead investors to shift their capital allocation away from firms and industries that are relatively more exposed to carbon pricing. The mechanism would help reallocating financial capital away from carbon-intensive and into low-carbon technologies and align financial markets with the climate objective.

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Appendix

Are global financial markets aligned with climate action? New Evidence from the Paris Agreement

Appendix A Descriptive Statistics by Subsamples

	Mean	Median	Std. Dev.	1^{st} perct.	5^{th} perct.	95^{th} perct.	99^{th} perct.	Min	Max
Daily Returns (in %)									
Top Green Firms (top 3 deciles)	-0.16	0	5.87	-12.82	-6.49	6.02	13.35	-163.14	268.17
Most Emissions Intensive firms (Scope 1) (top decile)	-0.21	0	3.46	-9.20	-4.41	3.44	7.92	-98.40	45.87
Most Emissions Intensive firms (Scope 2) (top decile)	-0.14	0	2.81	-7.35	-4.05	3.49	7.38	-98.40	28.04
Firms in top decile of clean Patent Intensity	-0.17	0	10.31	-13.28	-4.30	3.40	15.42	-230.26	230.26
Market Capitalization (in million USD)									
Top Green Firms (top 3 deciles)	2,147.29	362,16	4286,54	14.06	21.83	11,965.28	20,834.07	14.061	20,834.07
Most Emissions Intensive firms (Scope 1) (top decile)	12,092.59	7060.63	13880.84	281.48	927.91	37244.7	75698.73	231.733	76608.17
Most Emissions Intensive firms (Scope 2) (top decile)	13,759.27	8792.16	13,373.65	784.762	927.91	39,373.53	60,226.28	784.76	75,698.73
Firms in top decile of clean Patent Intensity	6,867.26	1,236.98	10,962.36	33.71	66.47	37,584.89	39,9953.48	33.707	39,9953.48
Average Market Capitalization of all listed domestic companies in the US (2013)	5,750.00	/	/	/	/	/	/	/	/
3-factor parameters									
r_{mt} (in %)	-0.04	-0.02	1.11	-2.95	-2.03	1.81	2.52	-3.9	3.68
r_{ft} (in %)	0	0	0	0	0	0	0	0	0
SMB (in %)	-0.05	-0.07	0.54	-1.35	-0.88	0.85	1.41	-1.66	1.82
HML (in %)	-0.03	-0.07	0.60	-1.23	-0.88	1.17	1.87	-1.49	1.99

Note: Daily values are for the period covered in the event study Event days [-121; +10]. Subsample market capitalisation is for 2013, the last pre-treatment year. The average market capitalisation of all listed domestic US firms is calculated by using World Bank Data and dividing the 2013 market capitalisation of listed domestic companies in the US by the total number of listed domestic companies in the US (The World Bank, 2019).

Table A.1: Descriptive Statistics

Appendix B Sector Distribution of Green Firms (top 3 deciles of Green firms) by 2-digit US SIC codes

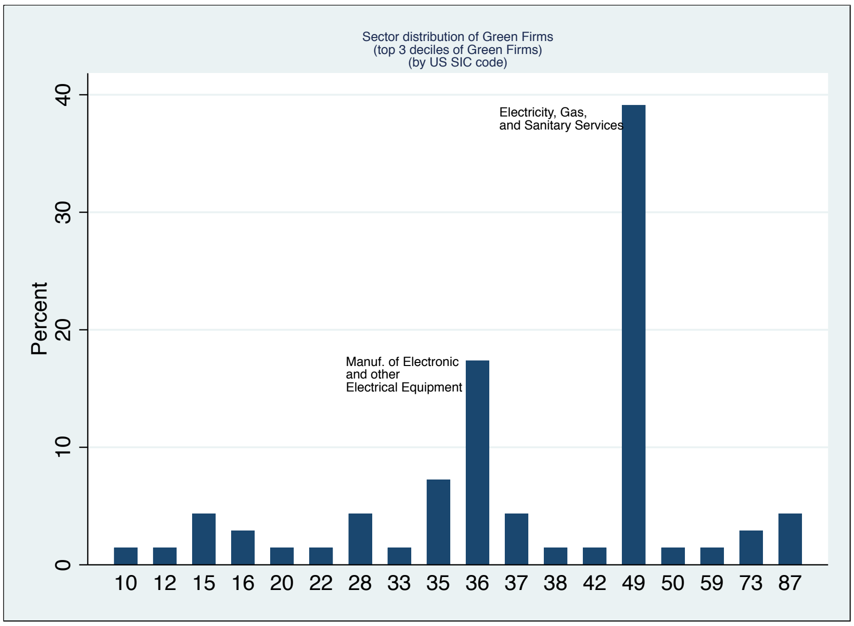


Figure B.1: Sector Distribution of Green Firms (top 3 deciles of Green firms) by 2-digit US SIC code

Note: The figure shows the sector distribution of Green Firms (top 3 deciles of Green firms) by 2-digit US SIC codes. The horizontal axis denotes 2-digit US SIC codes. The codes correspond to the following sectors. (10) Metal Mining, (12) Bituminous Coal and Lignite Mining, (15) Building Construction General Contractors and Operative Builders, (16) Heavy Construction other than Building Construction Contractors, (20) Manuf. of Food and Kindred Products, (22) Manuf. of Textile Mill Products, (28) Manuf. of Chemicals and Allied Products, (33) Primary Metal Industries, (35) Manuf. of Industrial and Commercial Machinery and Computer Equipment, (36) Manuf. of Electronic and other Electrical Equipment and Components, except Computer Equipment, (37) Manuf. of Transportation Equipment, (38) Manuf. of Measuring, Analysing and Controlling Instruments, (42) Motor Freight Transportation and Warehousing, (49) Electric, Gas, and Sanitary Services, (50) Wholesale Trade - Durable Goods, (59) Misc. Retail, (73) Business Services, (87) Engineering, Accounting, Research, Management, and related. services.

Appendix C Sector Distribution of Green Firms (top 3 deciles of Green firms) by 3-digit US SIC codes

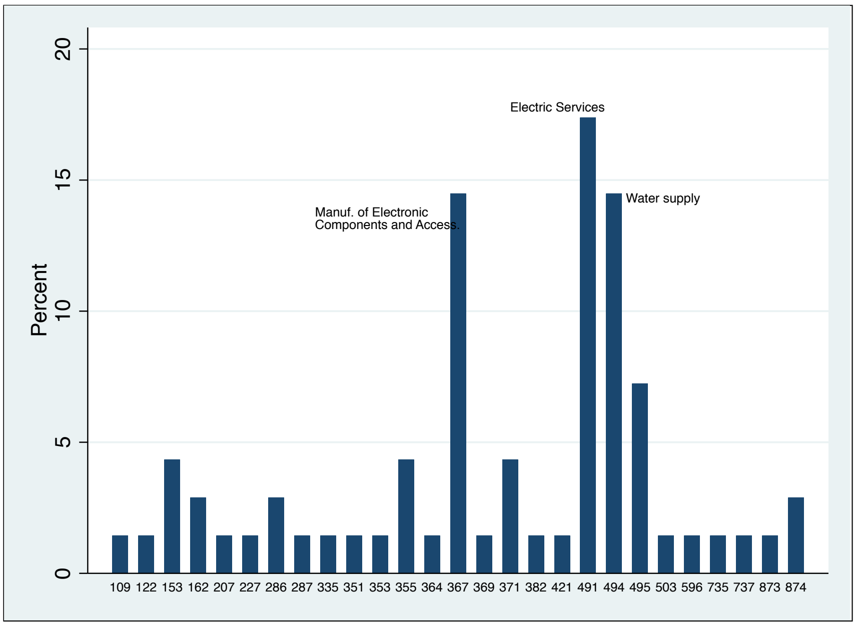


Figure C.1: Sector Distribution of Green Firms (top 3 deciles of Green firms) by 3-digit US SIC code

Note: The figure shows the sector distribution of Green firms (top 3 deciles) by 3-digit US SIC codes. The horizontal axis denotes 3-digit US SIC codes. The codes correspond to the following sectors. (109) Misc. Metal Ores, (122) Bituminous Coal and Lignite Mining, (153) Operative Builders, (162) Heavy Construction, exc. Highway and Streets, (207) Manuf. of Fats and Oils, (227) Carpets and Rugs, (286) Industrial Organic Chemicals, (287) Agricultural Chemicals, (335) Rolling, Drawing, and Extruding of Nonferrous Primary Metals, (351) Engines and Turbines, (353) Construction, Mining, and Materials Handling, (355) Spec. Industry Mach., exc. Metalworking, (364) Elect. Lighting and Wiring Equipm., (367) Electronic Components and Accessories, (369) Misc. Electr. Mach., Equipm., Supplies, (371) Motor Vehicles and Motor Vehicle Equipm., (382) Laboratory App. and Analytical, Optical, Measuring and Controlling Instr., (421) Trucking and Courier Services, exc. Air, (491) Electric Services, (494) Water Supply, (495) Sanitary Services, (503) Lumber and other Construction Materials, (596) Nonstore Retailers, (735) Misc. Equipm. Rental and Leasing, (737) Computer Program., Data Processsing, and other Computer Related Services, (873) Research, Development, and Testing Services, (874) Management and Public Relations Services.

Appendix D Event Path for Green firms (top 3 deciles) excluding public utilities: Electricity, Gas, and Sanitary Services (SIC 49)

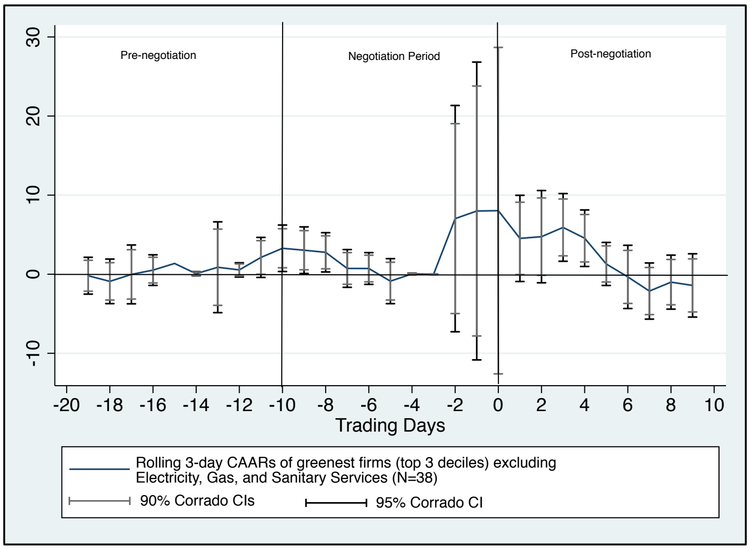
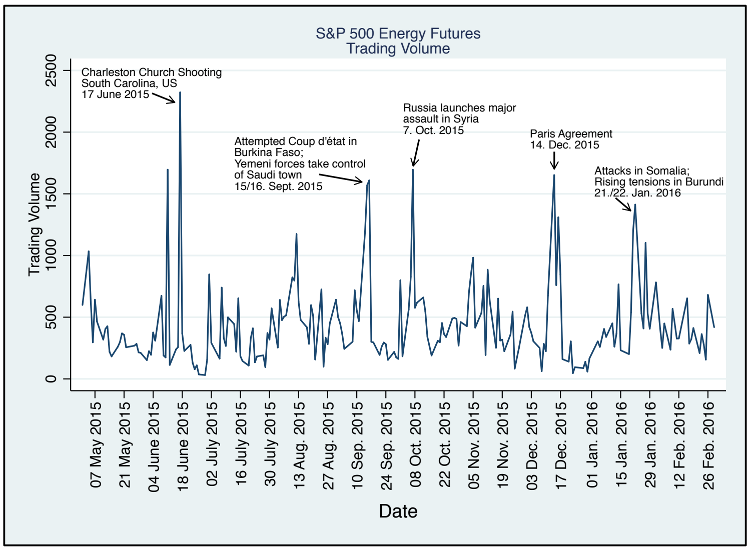


Figure D.1: Event Paths for Green firms (top 3 deciles) excluding public utilities: Electricity, Gas, and Sanitary Services (SIC 49)

Note: The figure shows 3-day rolling CAARs for green firms (top 3 deciles exlcuding public utilities: Electricity, Gas, and Sanitary Services (excl. SIC 49, N=38). The blue line shows the CAARs. The black bars are 95% Corrado-Cowan confidence intervals. The grey bars are 90% Corrado-Cowan confidence intervals.)

Appendix E S&P 500 Energy Futures Trading Volume



Note: This figure shows the trading volume of S&P500 Energy Futures. After a careful news search, the authors decided that the indicated events appeared to be the most significant and likely drivers of the trading volume. This does however not imply that the spikes were caused by the respective events.

Figure E.1: S&P 500 Energy Futures Trading Volume

Appendix F Google Trend Statistics

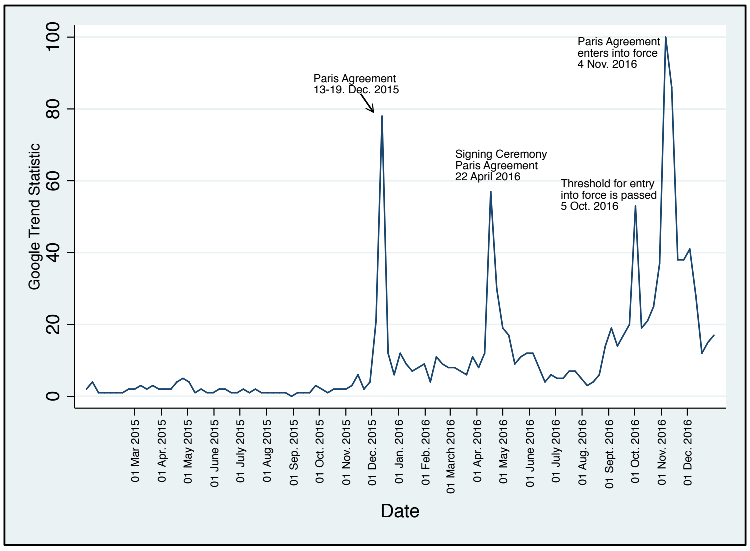
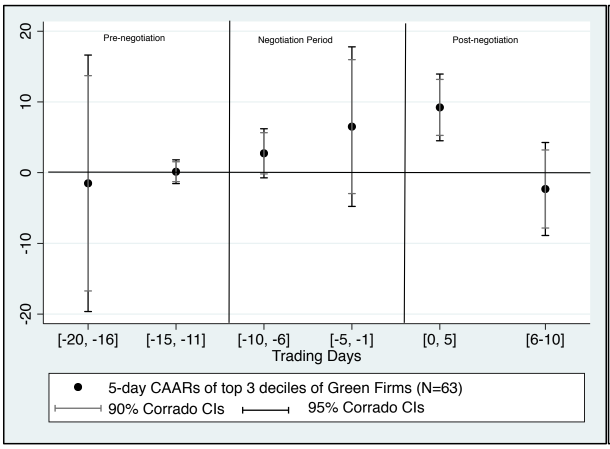


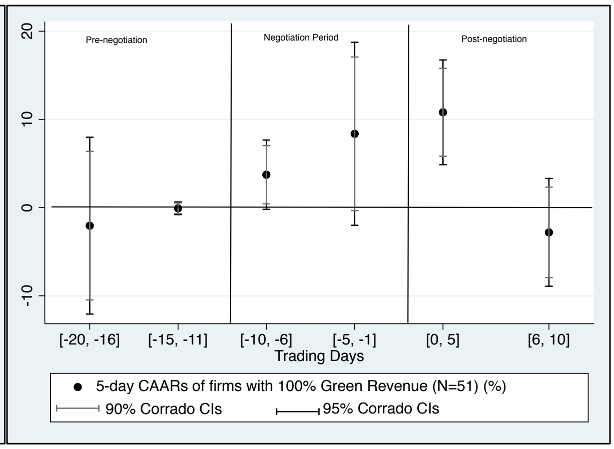
Figure F.1: Google Trend Statistics for the term 'Paris Agreement' (searched for in the US between March 2015 and December 2016).

Note: This figure shows the Google Trend Statistic for the term "Paris Agreement" searched for in the US between March 2015 and December 2016.

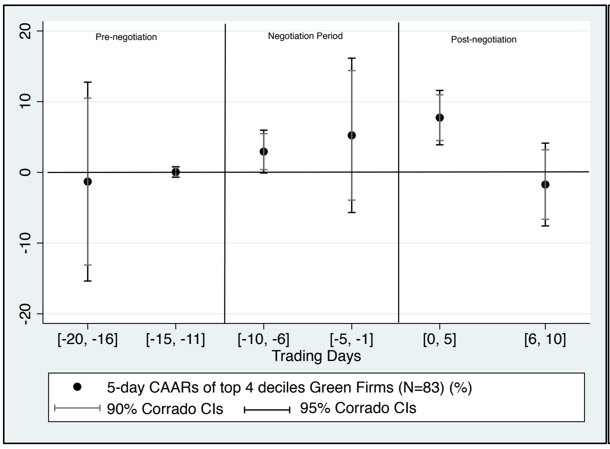
Appendix G Results with 5-day CAARs



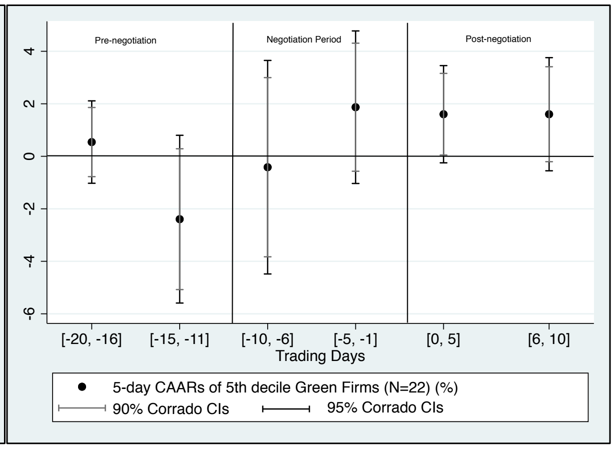
(a) Top 30% green firms



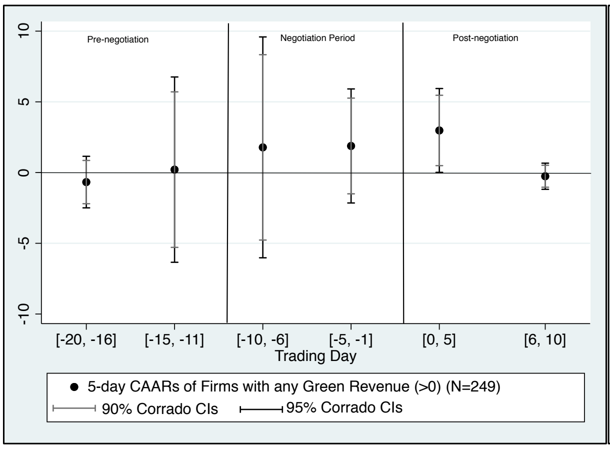
(b) Firm with 100% GR



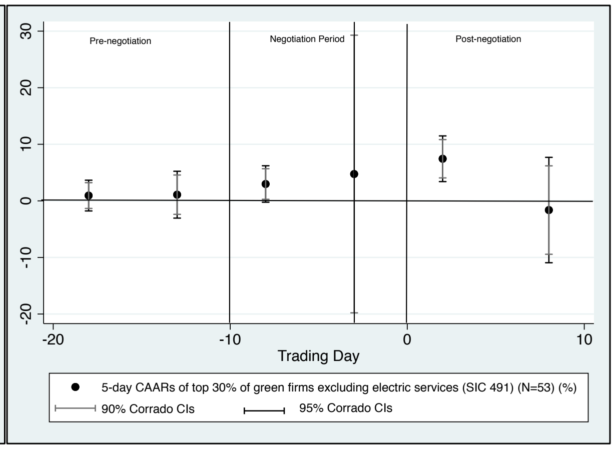
(c) Top 40% green firms



(d) Median (5th) decile of green firms



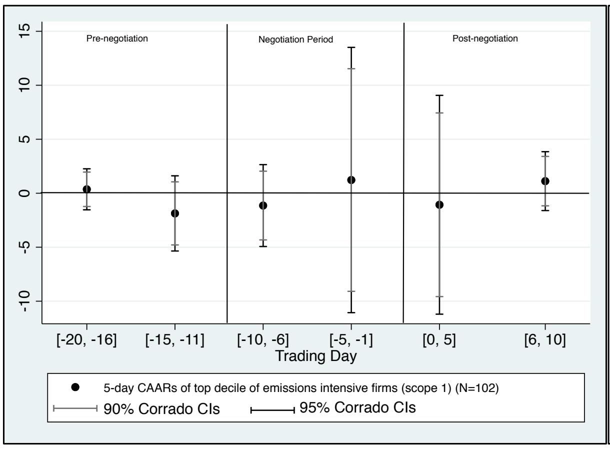
(e) Any green revenue (>0) between 2009-13



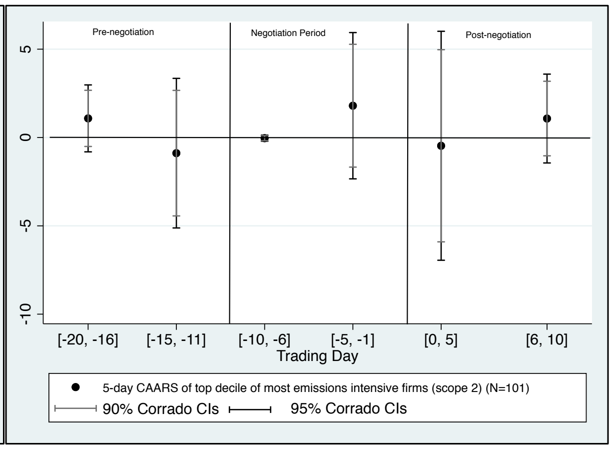
(f) Top 30% of green firms excluding electricity generation (SIC 491)

Figure G.1: Results with 5-day Cumulative Average Abnormal Returns (part 1)

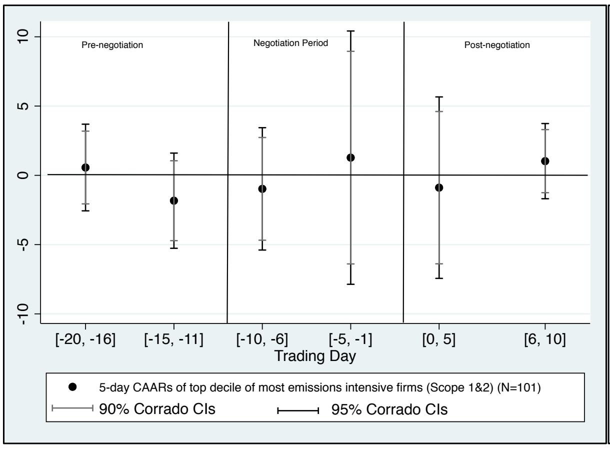
Note: This figure shows the 5-day CAARs of the different green portfolios. The black (grey) bars are 95% (90%) Corrado-Cowan confidence intervals.



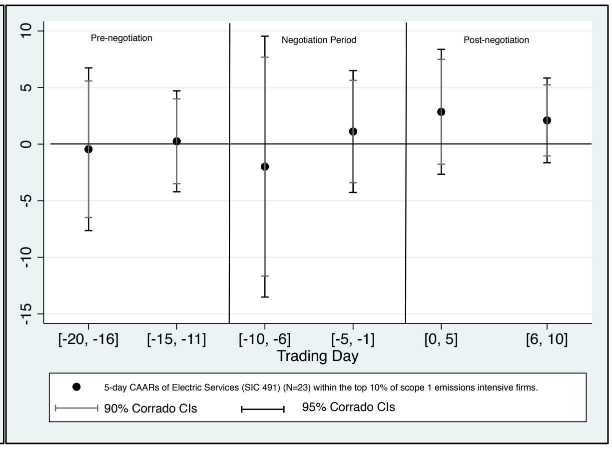
(a) Top 10% of most emissions intensive firms (Scope 1)



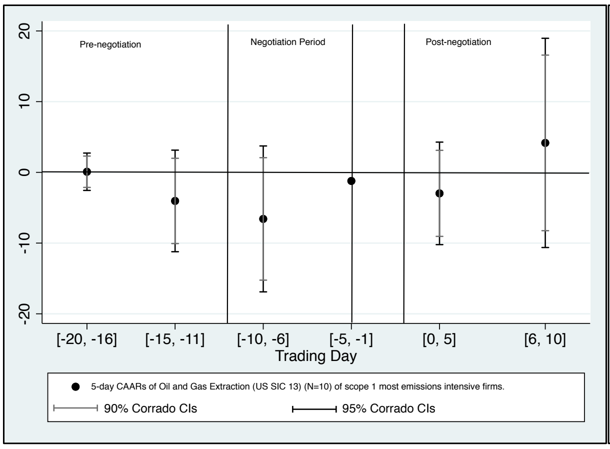
(b) Top 10% of most emissions intensive firms (Scope 2)



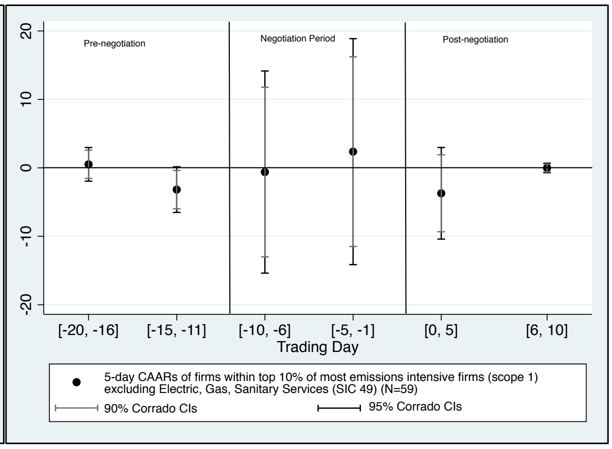
(c) Top 10% of most emissions intensive firms (Scope 1&2)



(d) Electric Services firms (SIC 491) among top 10% of most emissions intensive firms (scope 1)



(e) Oil and gas extraction (SIC 13) firms among top 10% of most emissions intensive firms (scope 1)

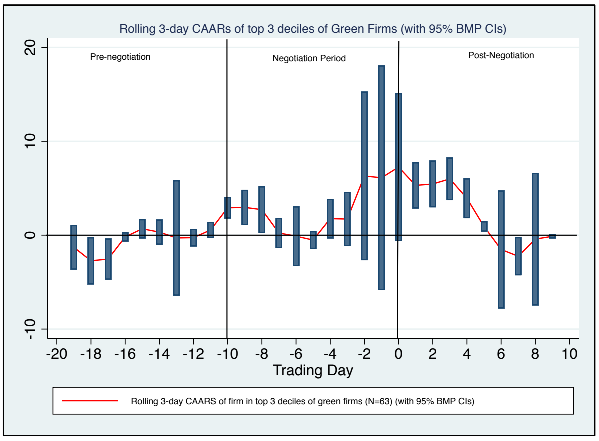


(f) Excluding Electric, gas and sanitary services (SIC 49) firms among top 10% of most emissions intensive firms (scope 1)

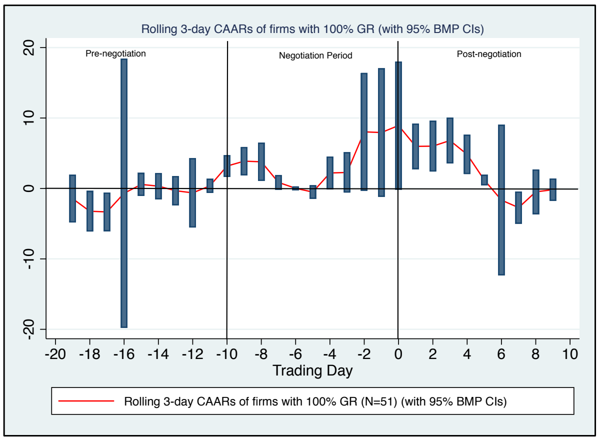
Figure G.2: Results with 5-day Cumulative Average Abnormal Returns (part 2)

Note: This figure shows the 5-day CAARs of the most emissions-intensive portfolios. The black (grey) bars are 95% (90%) Corrado-Cowan confidence intervals.

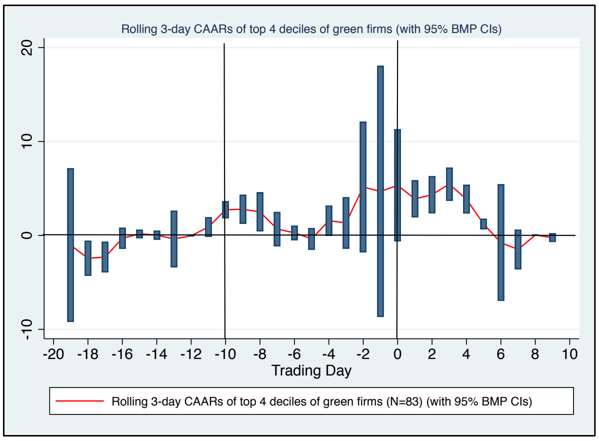
Appendix H Robustness Check using the BMP test statistic (developed by (Boehmer et al., 1991))



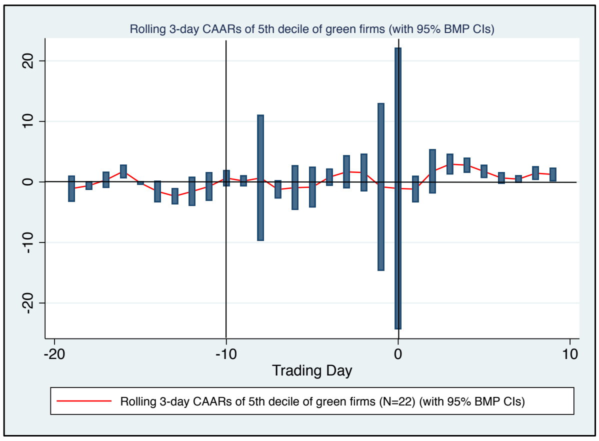
(a) Top 30% green firms



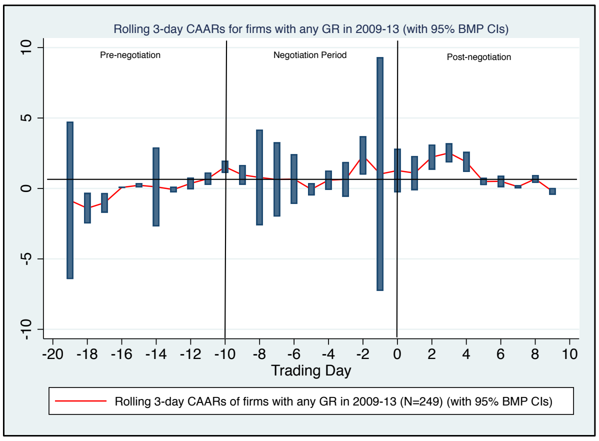
(b) Firm with 100% GR



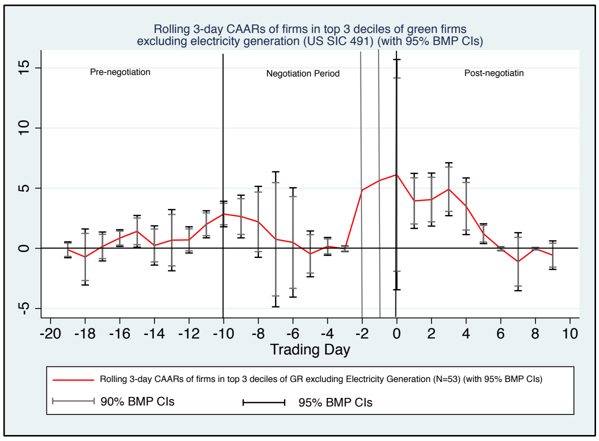
(c) Top 40% green firms



(d) Median (5th) decile of green firms



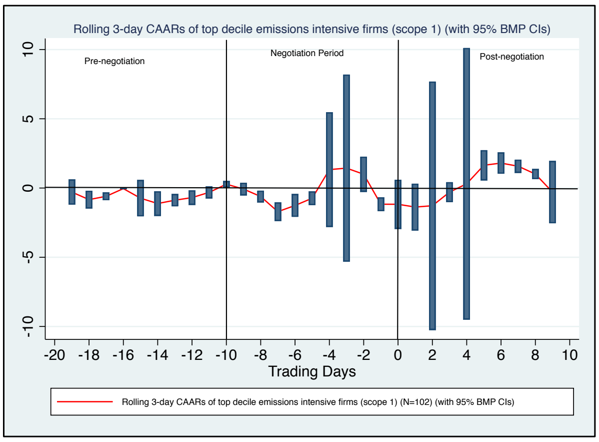
(e) Any green revenue (>0) between 2009-13



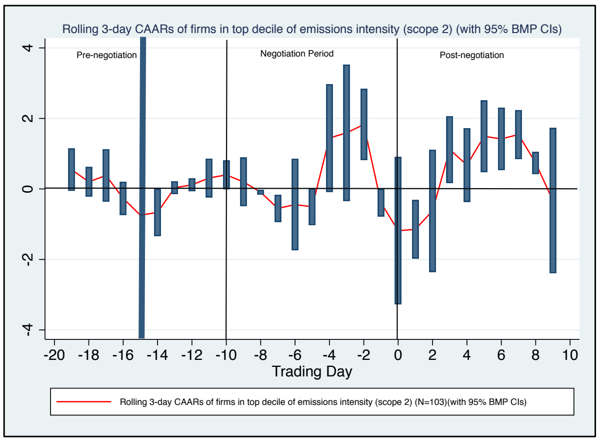
(f) Top 30% of green firms excluding electricity generation (SIC 491)

Figure H.1: Robustness checks using BMP test statistic (developed by (Boehmer et al., 1991)) (part 1)

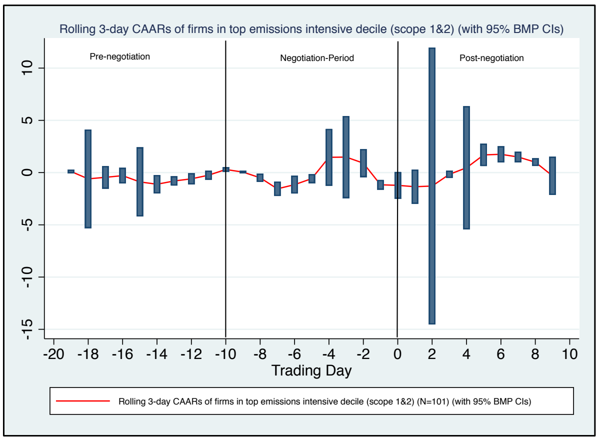
Note: This figure shows the 3-day CAARs of the different green portfolios with BMP confidence intervals.



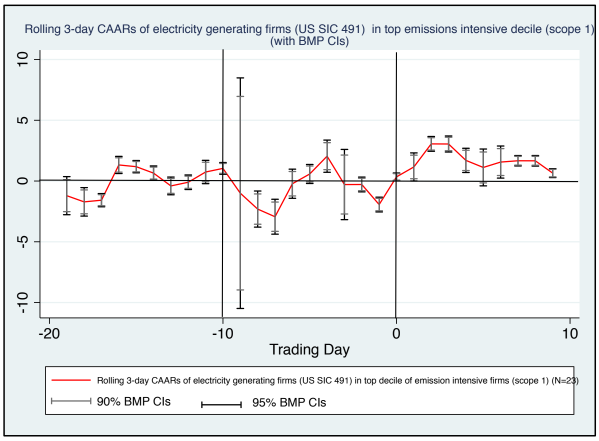
(a) Top 10% of most emissions intensive firms (Scope 1)



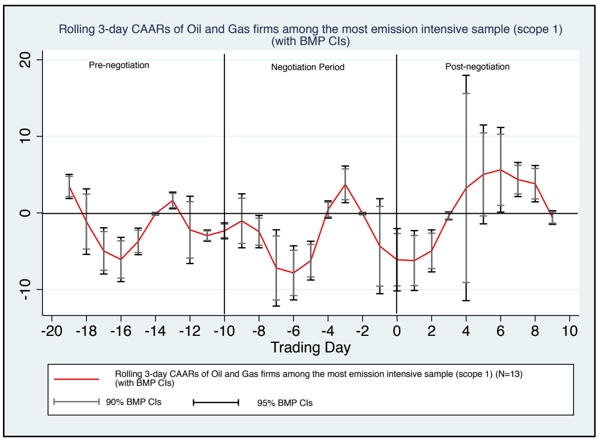
(b) Top 10% of most emissions intensive firms (Scope 2)



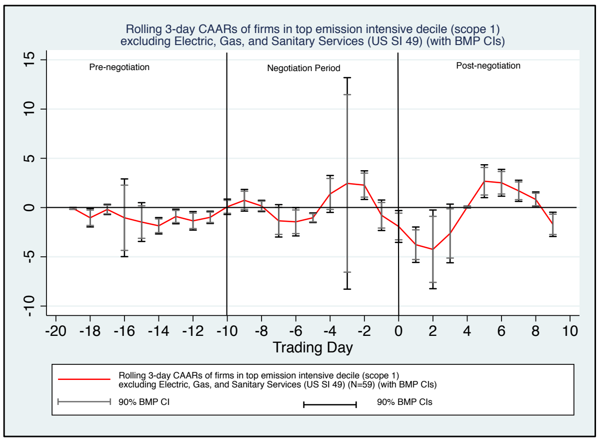
(c) Top 10% of most emissions intensive firms (Scope 1&2)



(d) Electric Services firms (SIC 491) among top 10% of most emissions intensive firms (scope 1)



(e) Oil and gas extraction firms (SIC 13) among top 10% of most emissions intensive firms (scope 1)

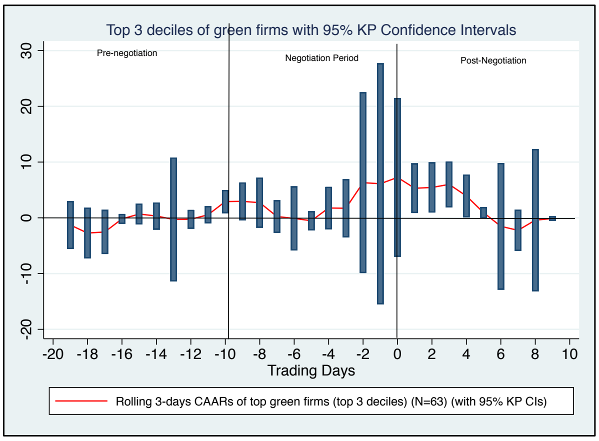


(f) Excluding Electric, gas and sanitary services firms (SIC 49) among top 10% of most emissions intensive firms (scope 1)

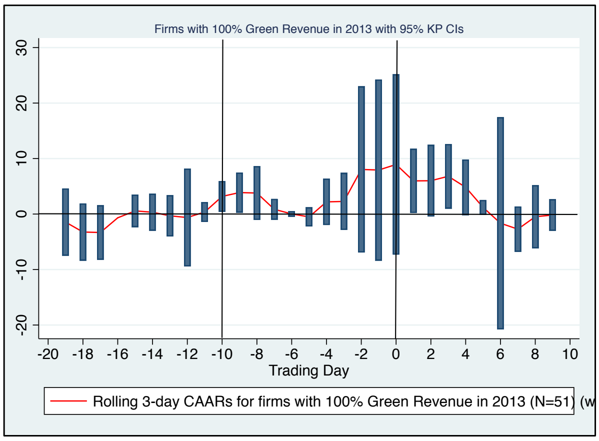
Figure H.2: Robustness checks using BMP test statistic (developed by (Boehmer et al., 1991)) (part 2)

Note: This figure shows the 3-day CAARs of the emissions-intensive portfolios with BMP confidence intervals.

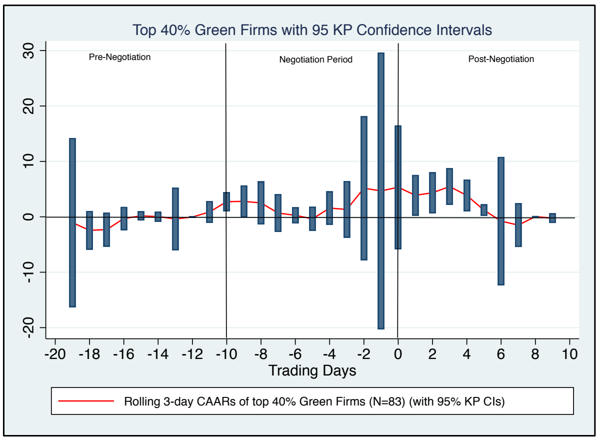
Appendix I Robustness Check using the KP test statistic (developed by (Kolari and Pynnonen, 2010))



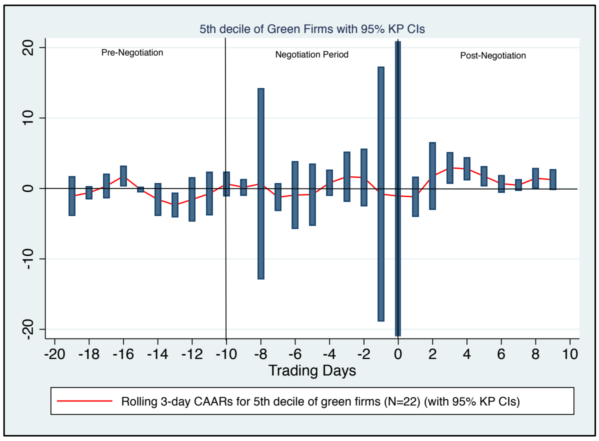
(a) Top 30% green firms



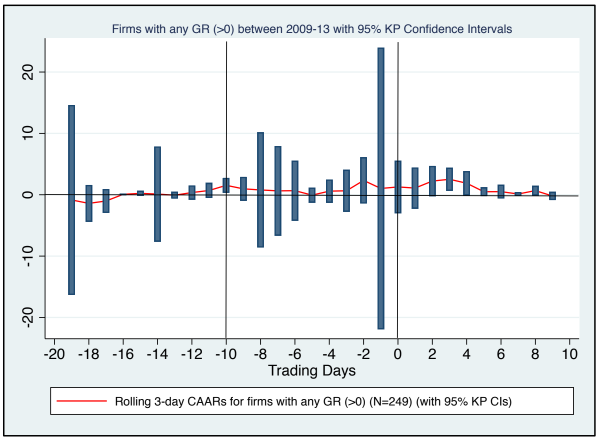
(b) Firm with 100% GR



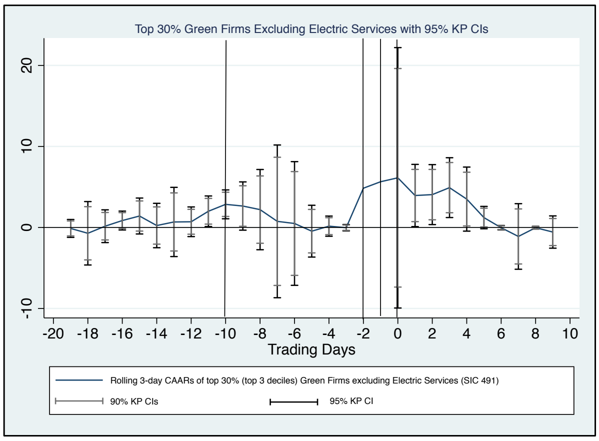
(c) Top 40% green firms



(d) Median (5th) decile of green firms



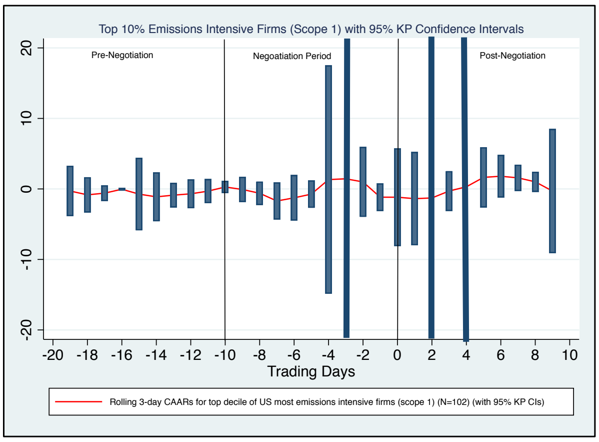
(e) Any green revenue (>0) between 2009-13



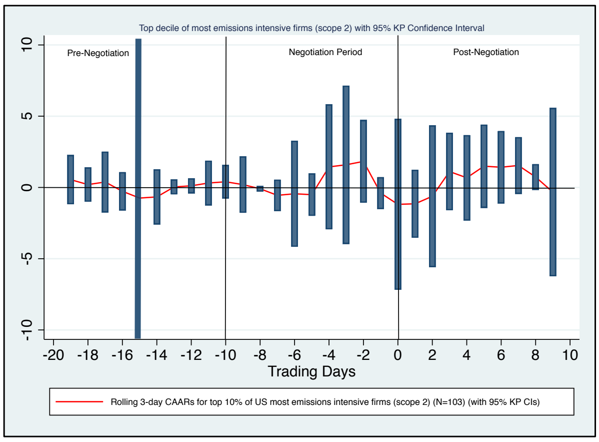
(f) Top 30% of green firms excluding electricity generation (SIC 491)

Figure I.1: Robustness checks using KP test statistic (developed by (Kolari and Pynnonen, 2010)) (part 1)

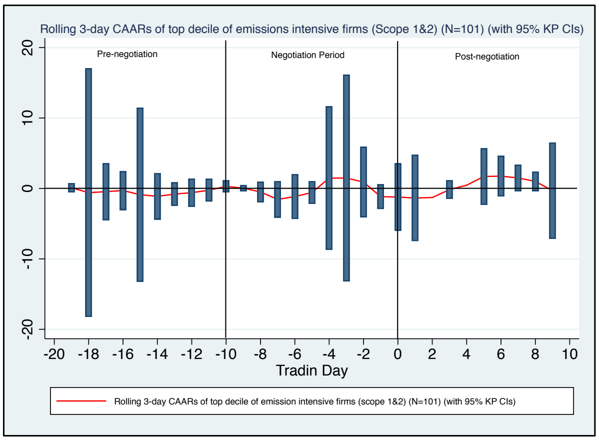
Note: This figure shows the 3-day CAARs of the green portfolios portfolios with KP confidence intervals.



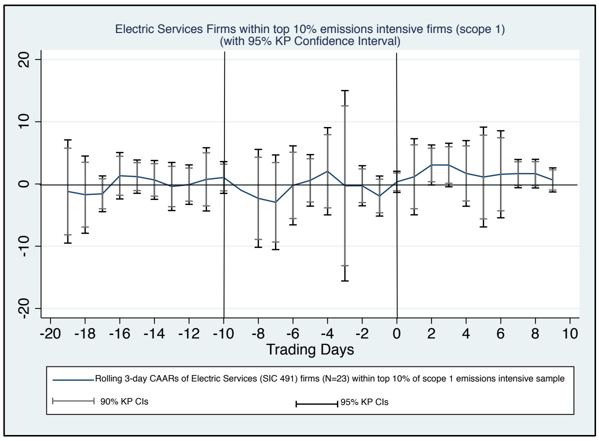
(a) Top 10% of most emissions intensive firms (Scope 1)



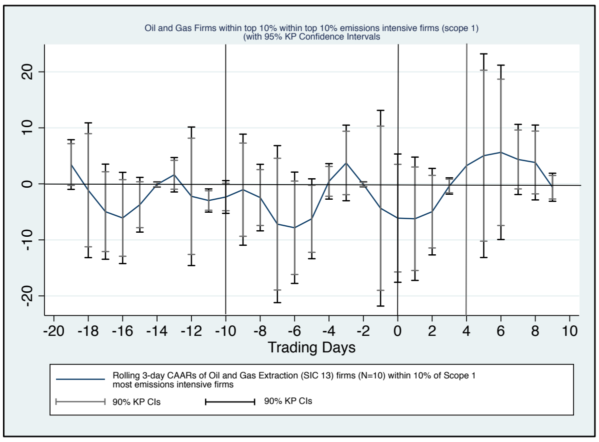
(b) Top 10% of most emissions intensive firms (Scope 2)



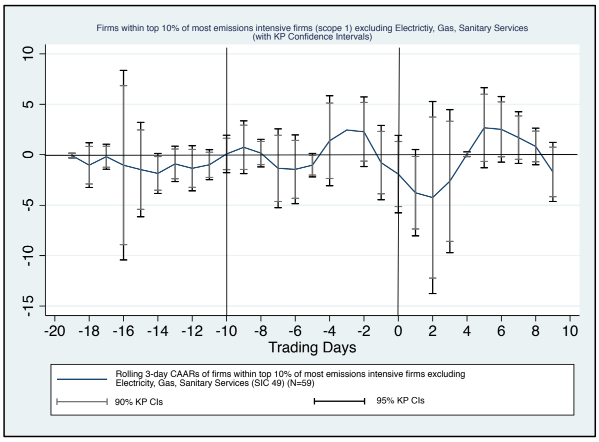
(c) Top 10% of most emissions intensive firms (Scope 1&2)



(d) Electric Services firms among top 10% of most emissions intensive firms (scope 1)



(e) Oil and gas extraction firms (SIC 13) among top 10% of most emissions intensive firms (scope 1)

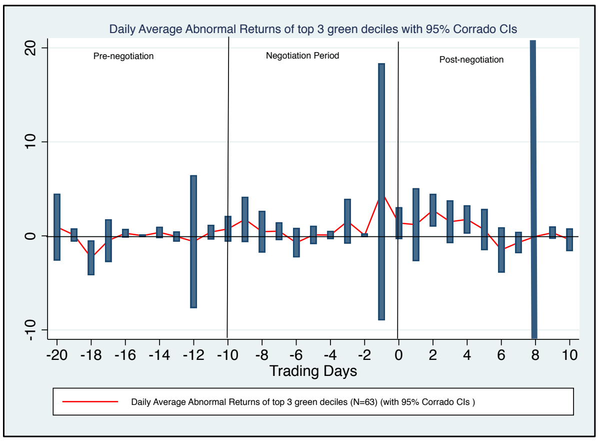


(f) Excluding Electric, gas and sanitary services firms (SIC 49) among top 10% of most emissions intensive firms (scope 1)

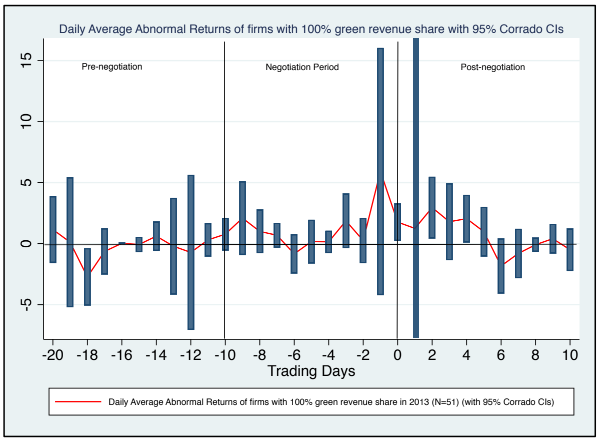
Figure I.2: Robustness checks using KP test statistic (developed by (Kolari and Pynnonen, 2010)) (part 2)

Note: This figure shows the 3-day CAARs of the emissions-intensive portfolios with KP confidence intervals.

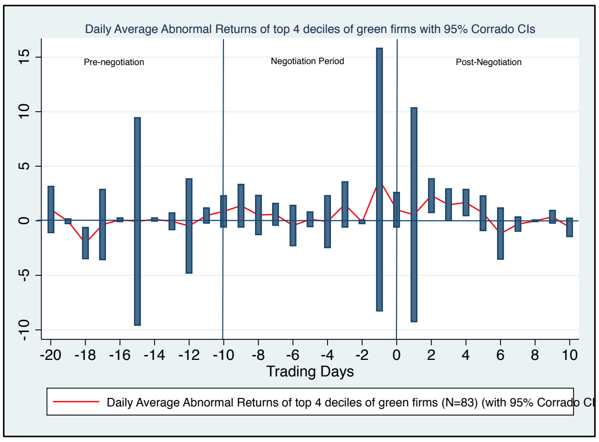
Appendix J Average Abnormal Returns (AARs)



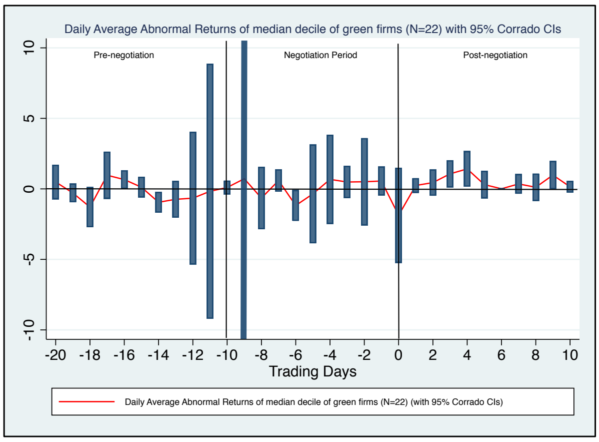
(a) Top 30% green firms



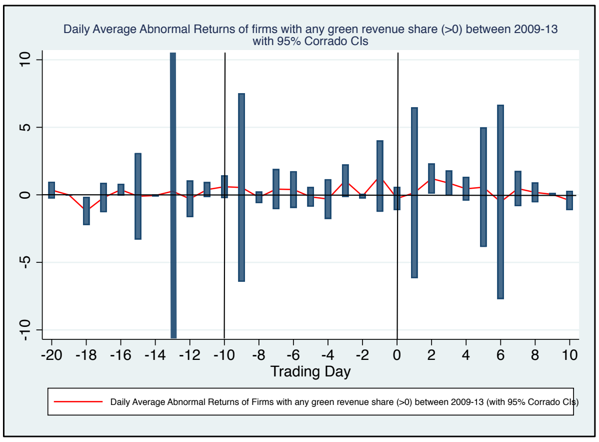
(b) Firm with 100% GR



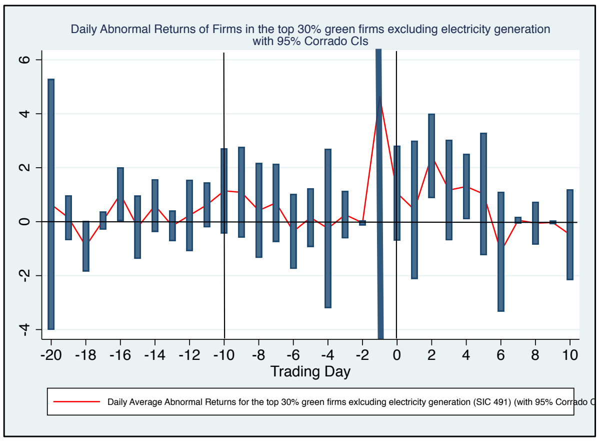
(c) Top 40% green firms



(d) Median (5th) decile of green firms



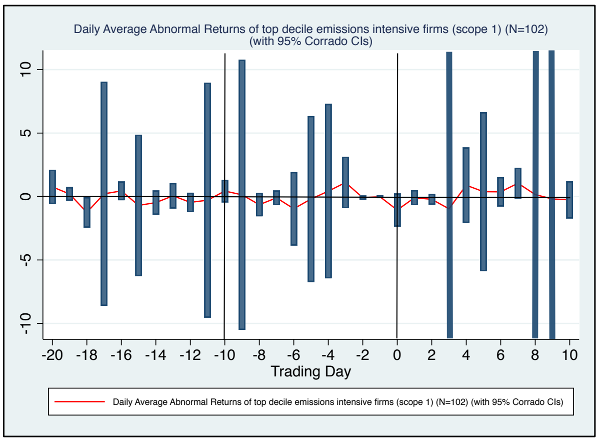
(e) Any green revenue (>0) between 2009-13



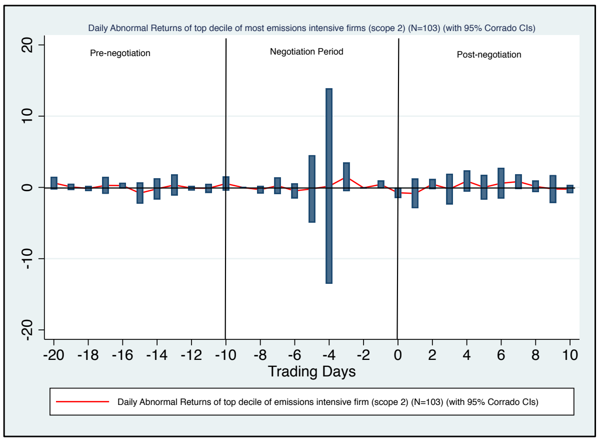
(f) Top 30% of green firms excluding electricity generation (SIC 491)

Figure J.1: Average Abnormal Returns (AARs) (part 1)

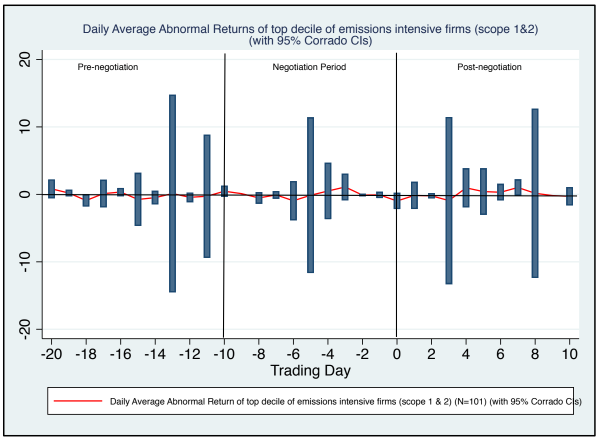
Note: This figure shows the Average Abnormal Returns (AARs) of the green portfolios with Corrado-Cowan confidence intervals.



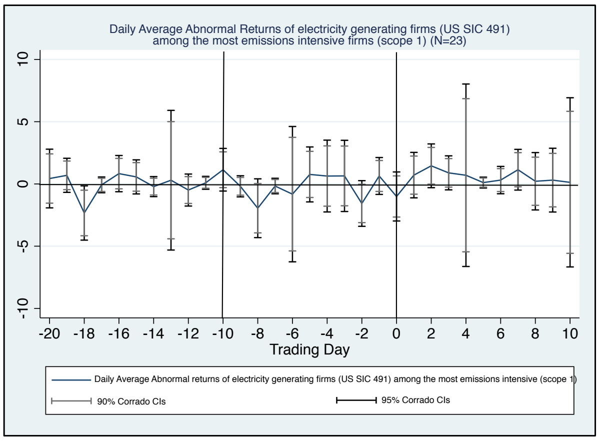
(a) Top 10% of most emissions intensive firms (Scope 1)



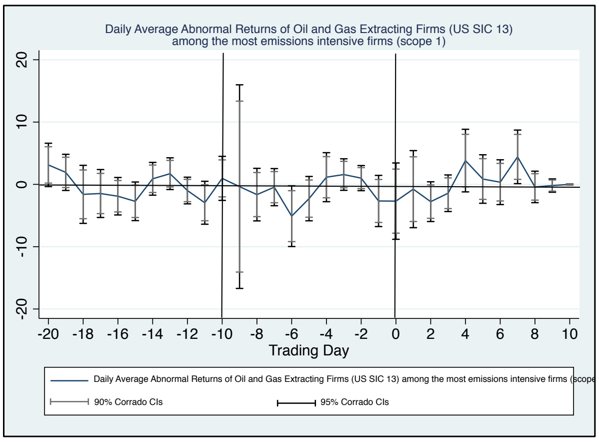
(b) Top 10% of most emissions intensive firms (Scope 2)



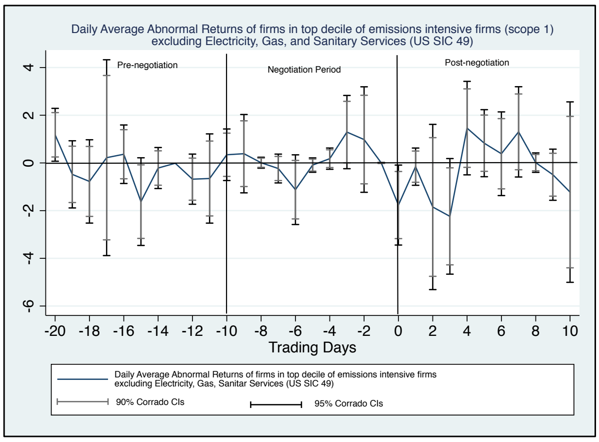
(c) Top 10% of most emissions intensive firms (Scope 1&2)



(d) Electric Services firms (SIC 491) among top 10% of most emissions intensive firms (scope 1)



(e) Oil and gas extraction firms (SIC 13) among top 10% of most emissions intensive firms (scope 1)



(f) Excluding Electric, gas and sanitary services firms (SIC 49) among top 10% of most emissions intensive firms (scope 1)

Figure J.2: Average Abnormal Returns (AARs) (part 2)

Note: This figure shows the Average Abnormal Returns (AARs) of the emissions-intensive portfolios with Corrado-Cowan confidence intervals.