The political economy of asset ownership: Evidence from the global power sector*

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Abstract

In this paper, we investigate how political shocks affect asset ownership in the global power sector. Therefore, we gather a unique dataset of 2 million global power plant-year observations including ownership information over time. In a DiD setting on the power plant level, we leverage the highly surprising first presidential election of Donald Trump as a quasi-exogenous change of the political orientation in the U.S. We find that foreign investors are more likely to sell US power plants to home-investors compared to a control group of global power plants. The effect is sizeable: the likelihood of this asset transaction increases by more than 7 percentage point for a given power plant. We find notable heterogeneity between brown and green US power plants: while foreign investors from liberal countries increase green power plant purchases, they reduce brown purchases. Home investors on the other hand only increase brown purchases. We explain the results by the interplay between the political distance of different investor groups to the new US ideology, as well as the changing climate preference of US investors. We demonstrate robustness of the main findings in a permutation test and in a matched sample. We extend the analysis to multiple right-wing populist elections in a stacked DiD setting and find that foreign-liberal investors sell brown power plants to home investors as a reaction to the elections.

Keywords: Political risk, climate transition risk, power plants, DiD, NLP

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1 Introduction

The last two decades brought unprecedented political change to the relatively stable post-war political economy of the Western world. The Brexit referendum or the elections of populist leaders such as Donald Trump or Boris Johnson are examples of profound political changes that may shape both economic and financial outcomes. Prior research shows that political shocks affect stock prices (Ramelli et al., 2021; Wagner et al., 2018), and impact households, corporate executives, and financial intermediaries' decision making (Kempf and Tsoutsoura, 2024). However, little is known about the impact of political shocks on the ownership of long-lived strategic assets.

In this paper, we investigate how a highly surprising and salient election shock (the election of Donald Trump as the 45th President of the United States of America in 2016) affects domestic and foreign investments in fossil and green power plants. We use the election of Donald Trump due to his strong political positions in favor of fossil fuels and against foreign ownership of strategic assets. We therefore expect heterogeneous reactions of home investors and foreign investors, moderated by the CO2 intensity of the power plant. The power sector is a unique setting to study the impact of political shocks on the ownership of risky assets due to two reasons: First, power plant owners are heavily exposed to political shocks since power plants are very long-lived fixed assets that cannot be moved away or easily retrofitted as a consequence of election shocks. Second, power plants are very relevant for the low carbon transition and therefore power plants are heavily exposed to climate policy driven transition risks. The power sector is responsible for more than a third of global GHG emissions[1] and other sectors decarbonization strategies heavily rely on the power sector. Compared to the confusion around measuring climate transition risk for financial securities, where popular metrics such as CO2 intensity and E-scores are criticized for being biased, incomplete and incomparable (Berg et al., 2022; Busch et al., 2022; Fliegel, 2026), the transition risk of power plants can be easily determined as both coal and gas power plants use GHG intensive fossil fuels, while renewable energies such as wind or solar produce energy with zero GHG emissions. Investments in the power sector are therefore highly exposed to (expected) climate policies (Hagen and Kollenbach, 2025). Sudden regulatory changes can lead to a reevaluation of brown/green asset values, which might in turn cause substantial losses/gains to exposed investors (Von Dulong et al., 2023; Ploeg and Rezai, 2020). Overall, power plants are regularly traded assets and investors can react to

[1] https://www.statista.com/statistics/276480/world-carbon-dioxide-emissions-by-sector/

(election) shocks by strategically increasing or decreasing the ownership in power plants with brown or green energy technology.

In line with recent research (Lin et al., 2026), we rely on a unique dataset of the global power plant fleet to answer our research question. The World Electric Power Plants (WEPP) dataset contains a global time series of roughly 2 million power plant year observations, including detailed plant information as well as the name of the largest owner - the parent. We leverage this dataset to analyze asset transactions between different types of investors over time. We carefully check asset transactions to rule out false positives in terms of asset sales. Most notably, we align parent names that refer to the same asset owner. We therefore rely on a Large Language Model (LLM) to align company names from similar parents. We then string match within the remaining parent list and align similar parents that are only spelled slightly different. Another challenge of the WEPP dataset is that it only contains the names of the parents. To gather information on both ownership type (listed, private, State-Owned-Enterprises (SOE)) and location of all asset owners, we match unique global parents with LSEG/Eikon and Orbis. For all parents that could not be matched, we use the WEPP company identifier to separate private unlisted companies from SOEs. For all remaining parents we leverage LLM-powered natural language processing to gauge ownership and location information based on the name of the parent. We finally obtain geographic information on all and legal status information on 96% of power plants owners. This detailed global coverage of both power plants and asset owners is going significantly beyond the previous focus of the literature on listed owners of power plants in industrialized countries. We split asset owners into five groups. As there are more domestic asset owners, we are more granular for home investors and split them into: Home-listed, home-private and home-SOE. We split foreign investors into liberal and conservative depending on their country of origin. We classify the political orientation of foreign investors according to the Manifesto database[2].

We first use the dataset to construct flow diagrams that descriptively show the ownership dynamics of US power plants over time depending on the energy technology. We provide three stylized facts on power plant ownership in the US from 2011 to 2021: First, the majority of brown and green assets are held by domestic asset owners. Home-listed investors are the largest asset owner for both green and brown power plants. Second, foreign investors from liberal countries own substantially more brown GW compared to foreign asset owners from conservative countries. For green power plants, liberal

[2] https://manifestoproject.wzb.eu/datasets

investors only own slightly more GW compared to conservative investors. Third, there is little asset trading between owners, relative to the overall ownership shares, that is, most owners keep their GW relatively stable year over year.

Next, we analyze in a plausibly causal setting how sudden changes in the political economy of the US impact the ownership of power plants in the US compared to a control group of global power plants. We leverage the election of Donald Trump in 2016 as a quasi-exogenous change of political orientation in the US. Our core empirical challenge is to disentangle the effect of the election shock on the ownership of power plants in the US. In our preferred empirical specification, we use a difference-in-differences (DiD) research design on the power plant level to compare the probability of a power plant to be sold/bought/newly constructed/decommissioned by a specific investor group in the US compared to a control group of international power plants, both before and after the treatment. Due to the granular power plant information of roughly 2 million installation-years, we can differentiate the treatment effect for brown (with separate analyses for gas and coal) and green power plants. By using both power plant and year fixed effects we run a tight empirical specification that compares the within power plant changes in the probability of being purchased/sold/newly constructed/decommissioned by a specific investor. We control for populist election spillovers as well as other political shocks in control countries by excluding assets owned by foreign investors, whose countries experienced comparably large political shocks.

Our first DiD results do not differentiate between different investor groups, but compare overall US power plant transactions, new constructions and decommissionings by energy technology with the rest of the world. We find a sizable Trump effect: First, overall trading volume in the US is increasing after the Trump election, compared to other countries. However, this effect is driven by coal and gas power plants, not renewable energies. Second, the Trump election shock leads to more brown power plant constructions, compared to the rest of the world. Green and renewable new constructions don‘t increase. Third, decommissionings increase for both renewables and coal, but not for gas power plants. Taken together, these results indicate that the Trump shock shifts asset transactions and new constructions towards brown power plants, green power plants are more likely to be decommissioned.

Our main finding is that foreign investors are more likely to sell and home investors are more likely to buy US power plants after the election shock. After 2017, the purchasing likelihood increases by 1.8 percentage points for home-private- and roughly 1 percentage point for home-SOE and 0.3 for home-listed investors for a given US power plant relative to the control group. Interestingly, conservative foreign investors, but not liberal foreign investors are more likely to buy a US power plant, as a results of the election shock. We also analyze the propensity of a power plant to be sold by a specific investor group. We find that conservative (liberal) foreign investors are 3 (10) percentage points more likely to sell a US power plant. Thus, liberal investors are more than three times as likely to sell a power plant compared to conservative investors. We also find a smaller but positive sales coefficient estimates for home-private and home-SOE investors, but not for home-listed investors. We finally go beyond aggregated asset sales and purchases and analyze transactions between specific buyer and seller pairs. Most notably, we find that the probability that a US power plant, that is held by a foreign investor, is sold to a home investors increases by a staggering 6.7 percentage points, while the probability that a home-owned plant is sold to a foreign asset-owner decreases by 1 percentage point. This effect is entirely driven by foreign-liberal investors who are more than 9 percentage points more likely to sell a US power plant after the election. The coefficient estimate for foreign-conservative investors is insignificant.

We also separately analyze the purchasing patterns for brown and green power plants for the five asset owner groups and in a triple DiD setting. The results for brown power plants mirror the effects for overall power plants: While foreign investors are more likely to sell, home investors are more likely to buy brown US power plants, compared to international power plants. Again, this effect is stronger for foreign-liberal investors, who are more likely to sell to home-investors compared to foreign-conservative investors. The coefficient estimate for foreign-liberal investors selling to home investors reaches 11 percentage points, showing the economic magnitude of the impact. Next, we interact the post and US dummy with a third dummy that is 1 for all brown power plants and 0 for all green power plants. The baseline DiD estimate shows that all foreign investors are more likely to buy green power plants, while home-listed and home-private investors show insignificant coefficient estimates. The triple interaction coefficient is positive and significant for both home-listed and home-private investors, indicating that these investor groups are only more likely to buy brown power plants, but not green power plants. The opposite is true for foreign-liberal investors, who are less likely to buy brown power plants. Home-listed investors are also significantly less likely to start new constructions of green US power plant, relative to control countries.

Our main results are robust to random treatment assignment, alternative empirical specifications and different sampling approaches. Most notably, we demonstrate robustness: (i) in a permutation test (ii) in a 1:1 matched sample (iii) in a restricted sample of OECD countries, (iv) in a restricted sample that does not rely on any LLM parent categorization, (v) in a full sample where no foreign investors are excluded due to political shocks in their home countries, (vi) and finally in a specification that uses unweighted observations.

Taken together, these results show that overall asset purchases by home investors from foreign investors increase after the election of Donald Trump. This indicates a re-nationalization of strategic assets, in line with Trumps election campaign rhetoric. However, this effect is moderated by both the ideological alignment of the asset owner, relative to the Trump administration (political alignment), as well as the climate preference of the investor group relative to Trump (climate alignment).

In terms of the political alignment of investors, we rationalize our findings by the ideological distance and political uncertainty for the respective investor group to the Trump administration. We argue, that home investors are most aligned, mirroring the "America First" approach of the Trump administration. Conservative foreign investors are more aligned compared to liberal foreign asset owners, as liberal investors from countries such as Sweden or Colombia face a substantial political distance to the new US administration. Investors from conservative countries such as Israel or Hungary on the other hand, are ideologically closer compared to the previous Obama administration. The political alignment of investors is closely mirrored by the treatment effects across investors, as home investors, across the board, are more likely to buy US assets. Conservative foreign investors buy more assets but also sell more US assets, implying a rather neutral reaction. Foreign-liberal investors increase asset sales substantially, while they do not purchase more US power plants.

The aforementioned pattern only holds for brown power plants, indicating that the Trump shock is not only moderated by the political distance of investors, but also shapes the technological preferences for different investors groups. While foreign liberal investors are more likely to buy green power plants, the same is not true for most home investors, which heavily increase the exposure to brown power plants. We hypothesize that brown power plants become more attractive for home-investors compared to green power plants after the election, because the Trump election changes home investors preferences towards brown power plants. This preference is in line with the new US administration, which left the Paris climate agreement and weakened climate policies[3]. Moreover, reputational risks are lower for home-investors when the President is personally advertising fossil fuels. Foreign investors, particularly liberal investors, on the

[3] See for example Ramelli et al., 2021 who show that fossil fuels stocks profited from the election of Donal Trump.

other hand, invest against the backdrop of increasingly stringent climate policies at home. Their preference is unlikely to be altered by an US election, therefore they are now less aligned in terms of climate preferences. Therefore home investors are more likely to buy into brown, and foreign investors are more likely to buy into green power plants.

We extend the analysis to seven more right-wing populist election shocks throughout the world[4]. We use a stacked DiD design with 3-year windows around the election year and find that foreign liberal investors are up to 7 percentage points more likely to divest brown power plants to home investors. The coefficient for foreign conservative investors is insignificant. These results show the external validity of the US results and highlight a new pattern: right-wing populist elections change the ownership dynamics of long-lived strategic assets in favor of home investors. This effect is moderated by the political and climate alignment of different investor groups with the new right-wing populist leaders.

With this paper on the impact of political shocks on the ownership of brown/green assets, we contribute to two distinct strands of literature. First, we contribute to a literature on the economic and financial impacts of political risks. Kempf et al., 2023 show that ideological alignment with foreign governments affects the cross-border capital allocation by U.S. institutional investors. Julio and Yook, 2012 find that political uncertainty in election years is associated with lower firm-level investments and reduced FDI in foreign affiliates (Julio and Yook, 2016). Bisetti et al., 2022 study close democratic wins in U.S. congressional races and find evidence for lower plant-level pollution and emission shifting to republican states. Baker et al., 2016 develop the Economic Policy Uncertainty Index and show that increased political uncertainty leads to declines in investment, output, and employment in the United States. Marx et al., 2024 document a positive effect of electoral turnovers on a countries economic performance. Finally, Funke et al., 2023 show that countries with new populist leaders on average have higher inflation, lower GDP and decreasing financial openness. Our study makes three important additions to this literature. First, we causally show that the election of a populist leader in the US leads to changes in the ownership of strategic long-lived assets, affecting green an brown assets differently. Second, we show that the ideological distance of different investor groups shapes these ownership changes. Third, we extend the ownership analysis towards an overall assessment of right-wing populist election

[4] The other right-wing populist were elected in Brazil, Bulgaria, India, Italy, the Philippines, the United Kingdom, and Poland.

shocks.

Second, we add to a literature that analyzes the impacts of transition risk shocks on the ownership and emissions of real assets. Duchin et al., 2024 investigate divestments of pollutive plants as a reaction to environmental pressure. Buyers of the pollutive plants are more likely to be private, less covered by ESG ratings, and headquartered in republican states compared to selling firms. Bartram et al., 2022 causally show that financially constraint firms shift CO2-intensive production away from states where climate policy increases suddenly. In an event study around the Paris Agreement Berg et al., 2023 show that large emitters reduced carbon emissions through divestments of pollutive plants. Green and Vallee, 2025 analyze the impacts of banks coal exit policies and find that heavily exposed borrowers have issues in financing their coal operations and are more likely to decommission coal power plants. Andersson, 2019 and Colmer et al., 2024 show that climate policies reduce national emissions. Darmouni and Zhang, 2024 descriptively study coal power plant ownership in Europe and find that state owned plants are slowest in scaling down. Finally, Dulong, 2023 investigates the asset stranding risk distribution of the global power sector, given certain decarbonization scenarios. We contribute to this literature by going beyond the analysis of assets in one specific market owned by listed investors. We compile data on all global power plants, including their non listed owners. We thereby significantly enlarge previous samples in terms of both analyzed assets and asset owners. We also analyze both green and brown assets, as previous work mostly focused on brown power plants, manufacturing facilities or aggregated emissions. We thereby show that the purchasing probability depends on the ideological and climate alignment of investors to the host country. We also extend this literature towards analyzing the effect of a policy event that decreases (as opposed to increases) transition risks for long-lived carbon intensive assets.

2 Institutional background and hypothesis development

Donald Trump won the Presidential elections in the United States on November 8, 2016. The election of Donald Trump was very surprising; all major polls projected a Clinton victory in the weeks before the election. The New York Times projected a Clinton victory with 85% probability[5]; betting markets closed at a 82% probability for

[5] https://www.nytimes.com/interactive/2016/upshot/presidential-polls-forecast.html?_r=0#other-forecasts

a Clinton victory[6], and FiveThirtyEight by Nate Silver gave Clinton a 71% probability before the election[7].

The magnitude of the political shock was very high since Trumps political views differed sharply from President Obama's in almost every political aspect: Trumps campaign promises followed a right-wing populist agenda. He supported economic protectionism and opposed free trade. He positioned himself strongly against immigration and put an emphasis on law and order. Further positions included corporate tax rate cuts and opposition to climate policies. The manifesto database constructs a left-right-ideology score from -100 to +100. The election of Donald Trump as President moved this score 40 points to the right. From 2011 to 2021, there are only three comparable election shocks[8] around the world, indicating the salience of the political shock.

We expect that the election of Donald Trump had a sizable impact on power plant ownership in the US due to two key political positions which differed sharply compared to the previous administration: First, Donald Trump is a radical supporter of fossil fuels and positioned himself strongly against renewable energies. His Campaign promises included withdrawing from the Paris Agreement and increasing the production and consumption of fossil fuels[9]. Second, his "America-First" campaign favored domestic investors over foreign investors, particularly for strategic or critical assets[10] such as power plants or grid infrastructure. We therefore expect that the political shock of his election changed investment preferences in the US for home and foreign investors. We also expect that his election changed the technological preference of home investors in the US.

We derive the following hypotheses: The first hypothesis describes the changing investment preferences for different investor groups that are more or less aligned with Trumps ideology: Following Trumps "America-First" position around critical assets and the increased uncertainty for foreign investors, particularly investors that are ideologically not aligned with the Trump administration, we first expect:

Hypothesis 1. *The election of Donald Trumps leads to a re-nationalization of power*

[6] `https://electionbettingodds.com/WIN_chart_maxim_lott_john_stossel.html`

[7] `https://fivethirtyeight.com/features/why-fivethirtyeight-gave-trump-a-better-chance-than-almost-anyone-else/`

[8] The three election shocks are the Austrian parliamentary election in 2017, the election of Jair Bolsonaro in Brasil in 2018, and the parliamentary election in Greece in 2019.

[9] `https://insideclimatenews.org/news/27052016/donald-trump-republican-party-election-fossil-fuels-coal-oil-gas-fracking-climate-change-paris/`

[10] `https://www.nytimes.com/2018/08/01/business/foreign-investment-united-states.html`

plants as foreign investors divest and home investors invest in US power plants.

The second hypothesis relates to the preference shift for home investors concerning emission intensity of power plants. Against the backdrop of Trumps strong preference for fossil fuels vs. renewable energies, we also expect:

Hypothesis 2. *The election of Donald Trumps leads to a stronger re-nationalization of brown power plants compared to green power plants as home investors adopt Trumps preference for brown power plants, but foreign investors don't.*

The third hypothesis is based on the interaction between political alignment and climate alignment of US power plant owners: We expect that the divestment effect is moderated by the ideological distance of foreign investors to the Trump administration as well as their brown and green preferences concerning power plant emissions. Given that conservative foreign investors are ideologically closer to Trump than liberal foreign investors, and that home investors develop brown preferences due to the Trump shock, compared to liberal-foreign investors, we expect:

Hypothesis 3. *The divestment of brown power plants is stronger for liberal foreign investors compared to conservative foreign investors. Foreign-liberal investors are relatively more likely to invest in green power capacity compared to home investors.*

3 Data & methodology

We first elaborate on how we construct the final power plant panel dataset; including investors location and ownership type. We then detail the causal empirical methodology to investigate the impact of the election of Donald Trump on power plant ownership.

3.1 Data

For this study we rely on different large string matched datasets.

World Electric Power Plants: The World Electric Power Plants (WEPP) dataset contains international data about power plants, with comprehensive coverage of all global power plants starting at .001 MW including all power technologies. The data are at the annual frequency from 2011 until the end of 2021 and show the main characteristics of the power plants (location, capacity and generating technology) as well as the largest owners and operators.

Our first objective is to identify asset sales. We define an asset sale as the change of the investor with the largest ownership stake. We track changes in ownership by comparing the exact parents names for a given plant over time. A naïve approach would categorize all parents name changes as a 'sale', however, upon reviewing the data it is obvious that asset owners rename frequently or that similar companies are written slightly different. Thus, this approach would generate ample false positives in terms of power plant ownership changes.

We overcome this challenge by first leveraging a LLM to align similar parent names. Most notably, we use ChatGPT o4-mini-high to check all 60,000 unique global power plant owners for similar names and similar parent companies[11]. We next align parent names through string-matching. In case we can match two or more parent names, we align the names to rule out false sales indications. Our rule for alignment is always towards a company, which was successfully matched to either LSEG or Orbis, with priority for listed companies. We verify all potential company name alignments through an LLM online web search. Next, we impute missing parent information when parent names are similar before and after the data gap. All remaining parent changes per power plant are now categorized as asset sales. From the original 86,780 identified asset sales, only 67,485 remain after the LLM alignment. After the string matching 62,277 final asset sales remain. A descriptive overview is provided in table 1.

Table 1: Asset sales

	Identified asset sales
Naive approach	86,780
After LLM alignment	67,485
After 1x1 matching	62,277

Note: This Table shows the identified ownership changes according to three different methodologies between 2011 to 2021. We define ownership changes as parent name changes.

We classify power plants into the categories brown (all fossil fuels) and green (renewables, hydro). However, we also establish the sub-categories: renewable, gas and coal. Critically, we only include active assets into the analysis. As active, we define assets that are under construction or operative. We also generate indicators for new constructions and decommissionings , however, each plant year observations, can only be a new construction or decommissioned once.

We classify the ownership type (private listed, private unlisted and SOE) as well as the country location of the power plants parent through matching the investor names to

[11] The prompt is provided in the Appendix.

company databases, relying on the WEPP company classification and leveraging AI.

First, we source the headquarter and ownership status from LSEG (formerly Refinitiv EIKON) and Orbis. For the roughly 2 million plant-year observations in our baseline dataset, we are able to match 900,000 to LSEG and another 200,000 to Orbis. Second, we rely on the WEPP company classifier for the remaining companies. The classifier categorizes the primary owners of the power plants into state-owned and private. However, the primary owner is not necessarily the largest owner, the parent, of the plant. We therefore only rely on this information when the parent is identical to the primary owner. This approach categorizes another roughly 630,000 observations into private unlisted and SOE. Third, for all remaining asset owners, we leverage multiple LLMs in order to gauge both location information as well as company ownership information. We first run all remaining unique parents through ChatGPT o4-mini-high to use natural language processing for each company name. Most notably, the LLM classifies asset owners based on the language of their name, locations displayed in the company name or legal identifiers, such as GmbH for unlisted German companies, into specific countries and ownership types. The LLM can also rely on the vast training set of information, which might include knowledge about parents in the WEPP dataset. By leveraging ChatGPT, we are able to classify the location of 600,000 more plant years as well as the ownership type of 90,000 additional firms. Next, we use DeepSeek to fill remaining data gaps[12]. As DeepSeek is developed by a Chinese company, we expect more information on Asian companies. Using DeepSeek resulted in geographic information for 85,000 and ownership type information for 30,000 parents. For the few remaining plant-year observations with missing investor country information, we assume that investor country equals asset country. Given that these asset owners are typically small, hold very little assets in terms of MW, and are thus not likely to be international investors, who would invest in oversees power plants, we argue that this assumption is justified.

As summarized in table 2, we are finally able to determine the ownership of 1,846,636 of the 1,931,937 plant-year observations in the dataset. In terms of investor location, we have full coverage. For the empirical analyses, we exclude all observations without ownership information.

The Manifesto election database: We match the asset owner countries with the Manifesto database (Lehmann et al., 2025), in order to categorize foreign investor coun-

[12] For both DeepSeek and ChatGPT we rely on the same prompt. The prompt is provided in the Appendix.

Table 2: Geographic and ownership classification

	Geographic information	**Ownership information**
LSEG	863,262	896,387
Orbis	193,641	193,949
WEPP classifier	-	634,911
ChatGPT	600,464	91,461
DeepSeek	85,869	29,928
Asset=investor	188,701	-
Total	1,931,937	1,846,636

Note: Table 2 shows the data sources for the classification of the parents across two dimensions: the location information of the parent and the legal ownership of the parent.

tries as either liberal or conservative. In line with Kempf et al., 2023, we use the party/president with the highest vote share as a proxy for the countries political orientation. Since the largest party may change with elections, we proxy the political orientation at the time of the Trump election shock by the last election before 2017, that is, the closest election to the US election shock. The variable of interest from the Manifesto database is the right-left-ideology (rile) score for each party. The election of Donald Trump, for example, shifted the US rile score from -6, indicating a moderately liberal political orientation towards 33, highlighting the extreme right-leaning political ideology of the Trump administration.

Power plant matching: As a robustness test, we address concerns related to different compositions of the power plant fleet in the US and the control countries, which might explain our findings. We therefore employ coarsened exact matching with a k-to-k restriction to enforce one-to-one matching within coarsened strata (Blackwell et al., 2009) in the year before the treatment, 2016, to ensure comparable samples across treatment and control group. We match based on four distinct power plant characteristics: MW, plant age, fuel-type and ownership type. This approach eliminates the need for weighting in subsequent analyses by pruning excess control observations, thereby creating a balanced sample that shares common empirical support across key covariates. Thereby, we can continue to MW-weight the observations even in the matched sample. Table 18 reports the pre- and post matching differences in all covariates. Results show significant differences before, and negligible differences after matching.

3.2 Empirical methodology

In order to identify the effect of political shocks on power plant ownership, we exploit the election of Donald Trumps as president in 2016. The election result was very unexpected with most pre-election polls projecting a Clinton victory. We also regard the potential impacts of this election on the power sector as highly salient, given the aggressive pro fossil fuel and anti foreign-investor position of his campaign. We therefore regard the Trump election shock as a salient and unanticipated event (Wagner et al., 2018; Ramelli et al., 2021) that increased the political uncertainty, and shifted the political orientation strongly to the right. We compare the asset ownership of power plants before and after treatment across treated power plants in the US as well as not treated plants in the rest of the world. The baseline specification for our parsimonious DiD estimation is this linear probability model:

$$Y_{it} = \beta_0 + \beta_1 \left(\mathrm{USA}_i \times \mathrm{Post}_t \right) + \mu_i + \mu_t + \varepsilon_{it} \tag{1}$$

where Y_{it} is a dummy that is 1 whenever a power plant i, during year t, is sold, bought, decommissioned or newly constructed by one of the five investor groups[13]. USA is a dummy that equals one for US power plants and zero if otherwise. The first media outlets called Trumps victory in the morning of November 9, 2016. Therefore, Post is a dummy that equals one for the year after the treatment date, the US election in 2016. We include both time (year) and power plant fixed effects into our baseline specification in order to to run a very tight causal empirical specification. Power plant fixed effects (μ_i) control for time-invariant differences across power plants such as, technology, location or MW. Year fixed effects (μ_t) capture common temporal shocks and seasonal trends. We cluster standard errors at the level of treatment assignment (Abadie et al., 2023), the country level. Finally, we weight power plant observations by MW to better reflect the vastly different power plant sizes ranging from 0.01 MW to 9.5 GW.

We also estimate a triple DiD analysis (Olden and Møen, 2022) that continues to compare the purchase probability of power plants between the pre- and post-treatment periods and between treated and control countries. What differs is that we leverage yet another difference in the power technology of the power plants, that is the difference between brown and green power plants. We implement the following triple DiD specification:

[13] The investor groups are home-listed, home-private, home-SOE, foreign-conservative and foreign-liberal

$$
\begin{aligned}
Y_{it} = \beta_0 + \beta_1 (\mathrm{USA}_i \times \mathrm{Post}_t) + \beta_2 \mathrm{Brown}_i + \beta_3 (\mathrm{USA}_i \times \mathrm{Brown}_i) \\
+ \beta_4 (\mathrm{Post}_t \times \mathrm{Brown}_i) + \beta_5 (\mathrm{USA}_i \times \mathrm{Post}_t \times \mathrm{Brown}_i) + \mu_i + \mu_t + \varepsilon_{it}
\end{aligned}
\tag{2}
$$

where β_5 measures how the treatment effect varies with the fuel technology of the power plant, i.e. a heterogeneous treatment effect.

Critically, we rely on different sub-samples for different estimations, that is, we only include the type of power plant that is relevant for the analysis. When we test, for example, the propensity of coal power plants to be bought or newly constructed by an investor, we only include coal power plants into the analysis. For asset sales and decommissionings , we go one step further and restrict the sample to the power plants held by a specific investor group since only these power plants can even be sold or decommissioned by that very investor[14].

Our econometric approach relies on the identifying assumption that the ownership trajectory of treated power plants would have continued to follow untreated plants in the absence of the US Presidential election. We argue that this parallel trends assumption is plausible when evaluating the effects of the election, given the large sample of power plants and asset transactions, the utilization of power plant fixed effects and the relative stability in ownership shares in most countries across time. The two most likely violations of the parallel trends assumption are, on the one hand: treated and control groups could be on different trajectories already before the event. On the other hand, different shocks in the power sector may differentially affect treatment and control group beyond the studied election. Concerning pre-trends in observable characteristics, we can test violations in the years before the treatment through event study type graphs. We show such figures in our results section. For our key results, parallel trends before the event hold.

Concerns related to other shocks depend on the national context as well as on their timing. The most straightforward violation are election shocks in control countries that change the political orientation strongly. Critically, populist election shocks may have become more likely as a result of the Trump election. To address both concerns we leverage the Manifesto database to identify comparable election shocks in control countries after the election of Donald Trump in late 2016. We conservatively classify a

[14] For example, when we analyze the likelihood that brown power plants from home-private investors are sold to a new owner, we only include brown power plants from home-private investors into the analysis.

right- or left rile election shock larger than (-)20 as the exclusion criteria, which is only half the US election shock. Based on this threshold, we exclude power plants held by investors from Austria, Brazil, Canada, Chile, France, Greece and Slovenia[15].

4 Results

We start by presenting descriptive results for the ownership of US power plants by energy technology. Then, we present results for the DiD estimations.

4.1 Power plant ownership dynamics in the US

We graphically highlight US power plant ownership over time by means of flow diagrams that show US power plant ownership for different investor groups over time. Therefore, we group asset owners into home-listed, home-private, home-SOE, foreign-conservative and foreign-liberal. There are three kinds of asset flows between these investor groups. First, assets can flow between owners - either an asset sale between different owners or a within owner flow. Second, newly constructed assets flow from a new construction category towards the respective new owner. Third, decommissioned power plants flow away from an asset owner towards the decommissioned category.

Fig.1 shows the ownership flows above 1 GW of brown power plants in the US. Most notably, the largest brown asset owner in the US, is domestically listed firms with above 300 GW in asset ownership. They reduce GW after 2013, but increase GW again in 2018. Home private investors are the second largest brown asset holder in the US. Interestingly, they strongly reduce the ownership of brown power plants from 260 GW in 2011 to 180 GW in 2021. Home listed investors on the other hand hold their brown power plant exposure constant over time. Foreign-liberal investors show an inverse behavior compared to home-listed investors, while they increase GW after 2012, they strongly reduce brown ownership after 2017. foreign-conservative investors only hold little brown GW in the US. Overall, US brown assets ownership remains relatively stable over time both within and across asset holders. When we zoom into coal and gas ownership in the US (fig. 5, fig. 6), we document high decommissionings for coal and only few new coal power plants constructions from 2011 to 2021. For gas, new constructions and decommissionings are roughly equal, therefore overall gas GW do not shrink in the US. The asset ownership for both coal and gas mirrors the asset

[15] In the robustness section, we show that results hold with and without this exclusion.

ownership for overall brown power plants.

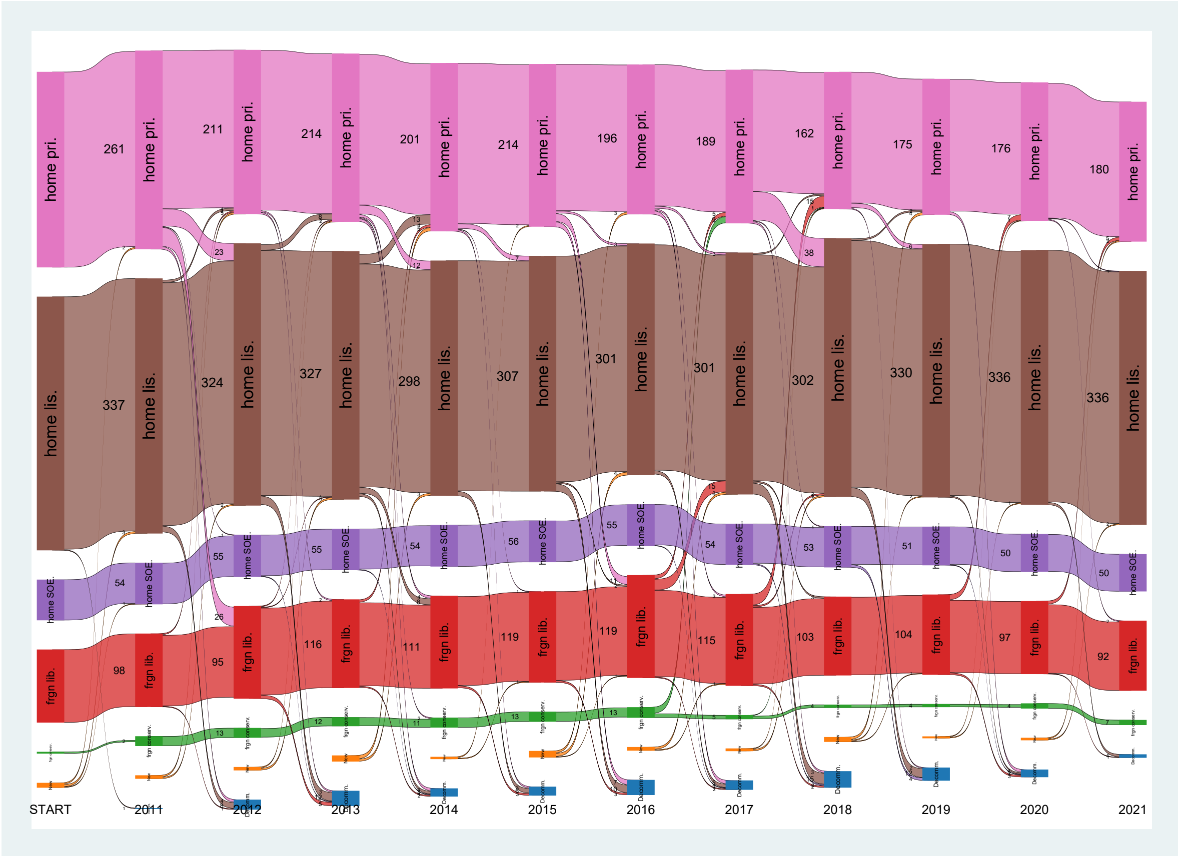

Figure 1: Flow diagram for brown power plants in the US from 2011 until 2021. The numbers in the figure indicate GW held by the respective owner. Asset flows below 1 GW are excluded for readability.

As depicted in fig. 2, the growth of US power demand is largely met by green assets, which grew strongly from 2011 to 2021. The largest owner of green US assets is, again, home listed owners, however, for green assets, home-SOE play a much more important role. They own roughly 37 GW of green power capacity, while home listed investors increase green GW from 45 GW to 95 GW. With the exception of home-SOE all green asset owners strongly invest in new green capacity over time. This indicates that home SOE rely on legacy capacity, but do not add new (renewable) power. In terms of relative additions, foreign investors are more aggressive compared to domestic investors, as both liberal and conservative foreign investors more than double their green GW from 2011 to 2021. Fig 7 shows the dynamic asset ownership for renewable energies. Interestingly, home-SOE only own very little, renewable GW, indicating that their green GWs are almost entirely composed of hydro power, a legacy green power source. All four other asset owners invest strongly in renewable capacity. As can be expected, the new construction category is significantly larger compared to the decommission category for renewable assets.

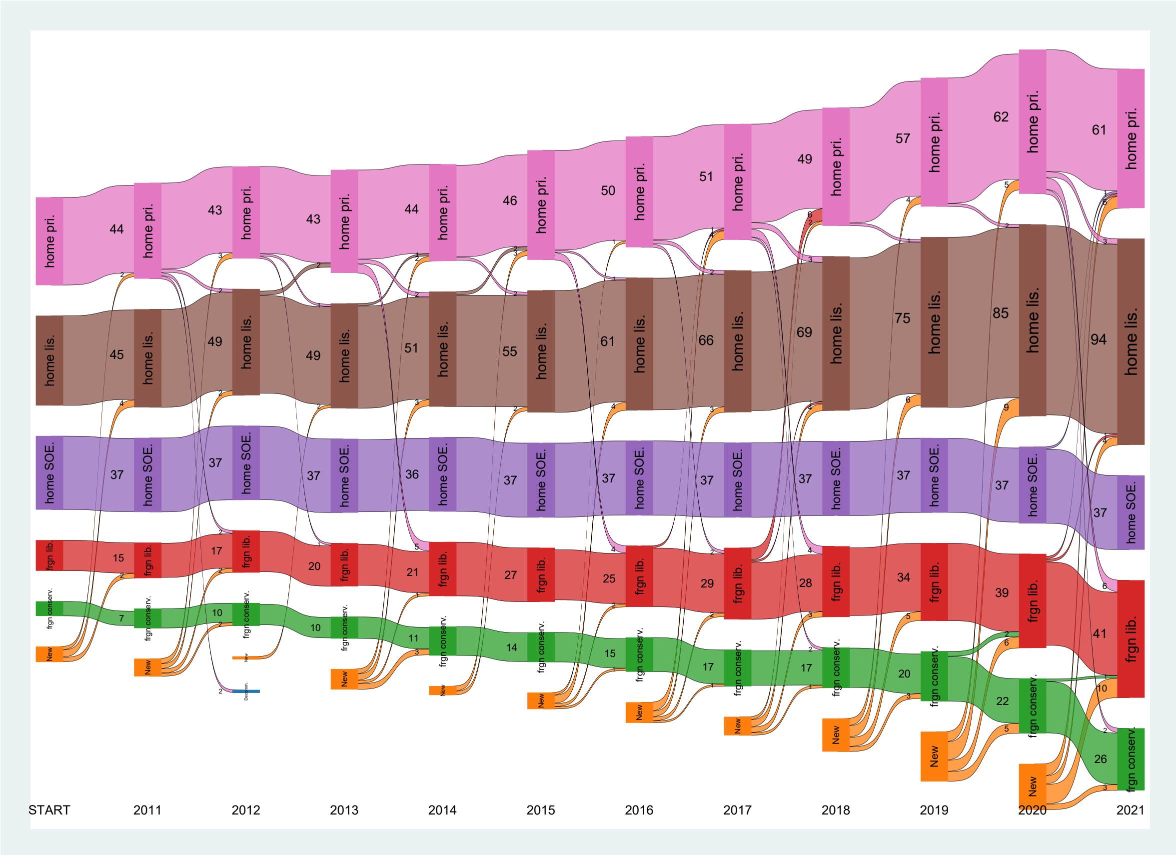

Figure 2: Flow diagram for green power plants in the US from 2011 until 2021. The numbers in the figure indicate GW held by the respective owner. Asset flows below 1 GW are excluded for readability.

4.2 The effect of the Trump election on overall power plant trading, new constructions and decommissionings

Our first causal did results do not differentiate between the five different investor groups, but investigate whether the purchasing, new construction and decommissioning probability of a given power plant increases as a result of the election shock, relative to the control group. As depicted in panel A of table 3, the likelihood of a US power plant to be purchased by a new parent increased by 2.7 percentage points as a result of the election shock, compared to a control group of international power plants. This effect is driven by brown power plants as the trading propensity of green power plants increases only by half compared to brown power plants. Interestingly, the only power plant category without a significant coefficient increase is renewable energies. Both coal and gas power plant trading increases by roughly 3 percentage points. As shown in panel B, overall new constructions also increase as a result of the election shock. Again the overall treatment effect of 1.5 percentage points is driven by brown power plants, as brown, coal and gas coefficients are all large and significantly positive, indicating that the Trump election led to a renewed interest in new brown, but not in new green, power plants. Finally, as reported in panel C, the probability of power plant decommissionings increases as well, however, overall coefficients are smaller compared to new constructions. Interestingly, the coefficient for gas is not significantly positive, but the coefficient for renewable energy is positive and significant. Thus, investors seem to keep older gas generation, but retire renewable capacity, while buying and constructing new brown power plants in the US, relative to the control countries.

Table 3: Effect of the 2016 US presidential election on overall power plant trading, construction and decommissioning

Panel A: Overall power plant trading probability by energy technology						
	(1) Overall purchases	(2) Brown purchases	(3) Green purchases	(4) Rnw. purchases	(5) Coal purchases	(6) Gas purchases
US*Post	0.027***	0.029***	0.017**	-0.003	0.031***	0.026***
	(0.005)	(0.005)	(0.007)	(0.011)	(0.004)	(0.010)
Power Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1586487	726761	764594	289176	99226	347993
Panel B: New construction probability by energy technology						
	(1) New construction	(2) Brown new construction	(3) Green new construction	(4) Rnw. new construction	(5) Coal new construction	(6) Gas new construction
US*Post	0.015***	0.022***	-0.005	0.006	0.034***	0.012***
	(0.005)	(0.007)	(0.004)	(0.011)	(0.009)	(0.004)
Power Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1586487	726761	764594	289176	99226	347993
Panel C: Decommissioning probability by energy technology						
	(1) Decommiss.	(2) Brown decommiss.	(3) Green decommiss.	(4) Rnw. decommiss.	(5) Coal decommiss.	(6) Gas decommiss.
US*Post	0.007***	0.010***	0.002***	0.003***	0.034***	0.001
	(0.002)	(0.004)	(0.000)	(0.000)	(0.004)	(0.002)
Power Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1586487	726761	764594	289176	99226	347993

Note: This Table shows DiD estimation results for the election of Donald Trump as President in the end of 2016 according to eq. (1). In panel A, the dependent variable is a power plants overall probability of being bought by a new parent, in panel B it is the probability of a new construction and in panel C it is a power plants probability of being decommissioned. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3 The effect of the Trump election on power plant ownership: the political alignment

We now focus on Hypothesis 1 and the political alignment channel. Therefore, we zoom into asset transactions by analyzing asset sales and purchases by investor category. As reported in panel A and panel B of table 4, foreign investors are more likely to sell and home investors are more likely to buy US power plants as a consequence of the Trump election shock. As hypothesized, the political alignment with the new administration moderates this effect, as foreign-liberal investors are almost 3x as likely to sell brown power plants compared to foreign-conservative investors. Foreign conservative investors on the other hand are more likely to buy brown power plants.

We can leverage the granular dataset further to go beyond broad asset sales and purchases and analyze sale-purchase combinations between pairs of investors groups. While assets can be bought and sold from the same type of investor (foreign-liberal sells to foreign-liberal), we are particularly interested in asset transactions between different types of parents. There are 20 potential asset flows between the five investor groups. In panel C, we report coefficient estimates for some key transactions. The overall probability of a foreign-investor owned US power plant to be sold to a home investor increases by almost 7 percentage points. The propensity of a foreign-liberal power plant to be sold to a home investor increases by almost 10 percentage points. The coefficient for foreign-conservative investors is insignificant.

We also analyze the evolution of the treatment effect over time by estimating a dynamic DiD model for the most relevant transactions: the likelihood of a foreign asset sale, a home asset purchase and an asset sale from a foreign investor to a home parent. Results in fig. 3 show no pre-trends in any pre-treatment coefficient year. The treatment effects in all three dynamic specifications are sizable and persist for up to 5 post-treatment years. Most notably, the probability for a foreign-home asset transaction in the US increases by roughly 10 percentage points in the two years after the surprising election. The effect is reduced in the post-treatment years three to five, but remains positive and highly significant. The persistence of the treatment effect indicates sustained changes in investments by home and foreign investors, even after Trump left office.

Table 4: Effect of the 2016 US presidential election on overall power plant ownership: Sales and purchases by investor group

	(1) Home-listed	(2) Home-private	(3) Home-SOE	(4) Foreign-conservative	(5) Foreign-liberal
Panel A: Sales by investor group					
US*Post	-0.008	0.065***	0.027***	0.032***	0.101***
	(0.008)	(0.013)	(0.008)	(0.011)	(0.005)
Power Plant FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	193813	574740	272664	121901	164420
Panel B: Purchases by investor group					
US*Post	0.003***	0.018***	0.010***	0.006***	-0.002
	(0.001)	(0.004)	(0.003)	(0.002)	(0.003)
Power Plant FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1586487	1586487	1586487	1112958	1112958
Panel C: Asset transactions between different investor groups					
	(1) Foreign→home	(2) Home→foreign	(3) Foreign-con.→home	(4) Foreign-lib.→home	
US*Post	0.067***	-0.009***	0.010	0.093***	
	(0.006)	(0.002)	(0.013)	(0.004)	
Power Plant FE	Yes	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes	
Observations	358553	1043449	121901	164420	

Note: This table shows DiD estimation results for the election of Donald Trump as President at the end of 2016 according to eq. (1). In panel A, the dependent variable is a power plant's probability of being *sold* by a specific investor group. In panel B, the dependent variable is a power plant's probability of being *bought* by a specific new parent. In panel C, the dependent variable is a power plants probability of being sold by a specific parent to a new specific parent. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

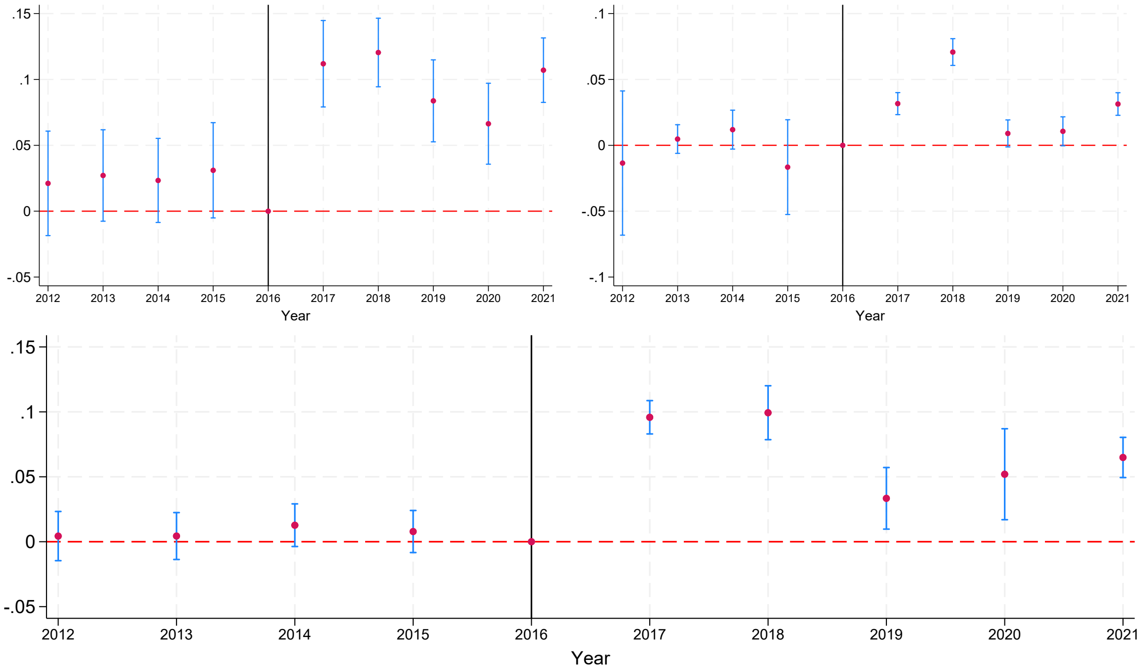

Figure 3: Summary event study figure of the election of Donald Trump as President in the end of 2016 for overall power plants. The dependent variable is a power plants probability of being sold by a foreign parent in the top-left panel. It is a power plants probability of being purchased by a home parent in the top-right panel. The bottom panel shows the treatment effect probability of a power plant that is sold by a foreign investor to a home asset owner. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021[16]. Standard errors are clustered at the country level.

4.4 The effect of the Trump election on power plant ownership: the climate alignment

We now investigate Hypotheses 2-3, that is, whether the heterogenous Trump effect on more or less aligned investors, is further moderated by the climate alignment of different investors groups to the Trump administration.

As reported in panel A of table 9, the likelihood of a brown power plant sale increases for all investors, but home-listed investors. Among foreign investors foreign-liberal investors are roughly twice as likely to sell brown power plants compared to foreign-conservative investors. The economic magnitude is sizeable: among brown power plants held by foreign-liberal investors, US power plants are 12 percentage points more likely to be sold, compared to power plants in control countries. This heterogeneity between foreign investors is in line with Hypothesis 3. panel B of table 9, complements the picture by analyzing the purchase probability by investor group. The results mirror the trends from the asset sales: while all home investors and foreign-conservative investors are significantly more likely to buy brown power plants, foreign-liberal asset owners probability remains flat. Taken together these effects indicate that home investors buy brown power plants from foreign investors in a re-vitalized market for brown power plant transactions. Foreign-liberal investors seem to be particularly eager to reduce their exposure to brown US power plants. panel C finally reports probabilities for decommissionings : only home-SOE are more likely to decommission power plants, all other coefficients are small and insignificant at the 5% level.

In table 5 we test Hypothesis 1 for brown power plants. We find that foreign investors sell brown power plants to home investors, in line with the notion of a re-nationalization of strategic long-lived assets in the US. The likelihood of this asset transaction increases by a staggering 8.3 percentage points. Interestingly, foreign investors do not only sell their power plants to home investors, they are also less likely to buy brown power plants from home investors. Again, this effect is stronger for foreign-liberal investors.

Table 5: Effect of the 2016 US presidential election on brown power plant ownership: Asset transaction between home and foreign parents

	(1) Foreign→home	(2) Home→foreign	(3) Foreign-con.→home	(4) Foreign-lib.→home
US*Post	0.083***	-0.012***	0.077***	0.107***
	(0.007)	(0.003)	(0.006)	(0.003)
Power Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	153134	489769	47845	66319

Note: This Table shows DiD estimation results for the election of Donald Trump as President in the end of 2016 according to eq. (1). The dependent variable is a brown power plants probability of being sold by a specific parent to a new specific parent. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In fig. 8, we show the dynamic treatment effect for brown power plants. There are no pre-trends in either of the three event study graphs before the surprising election. For foreign brown asset sales, all post-event coefficient estimates are significant and positive at the 5% level. The coefficient estimates amount to 15 percentage points and persist for up to 5 post event years. The coefficient estimates for brown home purchases fluctuate between 2-10 percentage points. The effect of the foreign-home asset transaction amounts to 10 percentage points in 2017 and 2018. The effect also persists for up to 5 post event years.

We can also zoom into every of the 20 asset transactions between the five asset owners. As reported in table 10, foreign-liberal investors are significantly less likely to buy brown power plants from two other investor groups. Conservative-foreign investors are less likely to buy brown power plants from one investor. Home-SOE investors buy more brown power plants from one other investor and home-private and home-listed investors are more likely to buy brown power plants from two other investor groups. Overall, the effects closely mirror the aggregated aforementioned results for brown power plant transactions between home and foreign investors.

Finally, we dissect the treatment effect for brown power plants into the two most relevant fossil fuels, coal and gas powered plants. Results for gas power plants are reported in table 11,table 12 and table 13 of the Appendix for asset sales, purchases and home-foreign transactions. The results show, again, that foreign-liberal investors are increasing asset sales strongly. Interestingly, foreign-conservative investors are significantly less likely to sell a gas power plants after the election shock, indicating that political alignment with the new Trump administration moderates the treatment effect. In terms of purchases, home-private, home-SOE and foreign-conservative investors are significantly more likely to buy gas power plants. As reported in fig. 9 the treatment effect for gas power plants that are sold from foreign investors to home-investors amounts to almost 15 percentage points. Dynamic coefficient estimates are not significantly different from zero for all pre-treatment years. Results for coal are relatively similar compared to the results for gas power plants[17]: Home investors and foreign-conservative investors are more likely to buy coal fired power plants after the election of Donald Trump, particularly from foreign investors. Parallel trends, hold for all pre-treatment time periods.

Next, we focus on different effects for brown and green power plants. Therefore, we estimate the triple DiD estimation provided in eq. (2) that takes a third difference for brown or green power plants. In line with Hypothesis 2, results in table 6 show that the energy technology of the power plant strongly moderates the treatment effect. The baseline effect for green power plants indicates that foreign investors are more likely to buy green power plants, while only home-SOE show a positive coefficient. This is contrary to the results in table 9 for brown power plants as home-investors were significantly more likely to buy brown power plants. The moderating effect of power plant fuel technologies is captured in the triple interaction effect: the coefficient is positive and highly significant for home-listed and home-private, but negative for foreign-liberal parents. This strongly suggests that home investors are only more likely to buy brown power plants, but not green power plants. Foreign-liberal investors on the other hand are more likely to buy green power plants, but less likely to buy brown power plants. We do not document a comparable effect for foreign-conservative investors. Thus, the Trump shock did not simply lead to a re-nationalization of assets driven by Trumps "America First" narrative, but the effect is moderated by the political and climate alignment of the respective investor - in line with Hypothesis 3.

[17] Results for coal power plants are provided in table 14, table 15, table 16 and fig. 10 of the Appendix.

Table 6: Effect of the 2016 US presidential election on power plant ownership: Purchases by investor group - triple interaction with brown and green power plants

	(1) Home-listed purchase	(2) Home-private purchase	(3) Home-SOE purchase	(4) Foreign-conservative purchase	(5) Foreign-liberal purchase
US*Post	-0.003	0.005	0.008**	0.004*	0.007**
	(0.002)	(0.003)	(0.004)	(0.002)	(0.004)
US*Post*Brown	0.010***	0.018***	0.001	0.004	-0.014***
	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)
Power Plant FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1491360	1491360	1491360	1048636	1048636

Note: This Table shows triple DiD estimation results for the election of Donald Trump as President in the end of 2016 according to eq. (2). The dependent variable is a power plants probability of being bought by a specific parent. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

New constructions play a pivotal role for green power plants. Therefore, table 7 shows the treatment effects for new green constructions. While no investor groups shows an increase in the probability at the 5% level, home-listed investors are significantly less likely to start a new green power plant construction.

Table 7: Effect of the 2016 US presidential election on power plant ownership: New constructions of green power plants

	(1) Home-listed new construction	(2) Home-private new construction	(3) Home-SOE new construction	(4) Foreign-conservative new construction	(5) Foreign-liberal new construction
US*Post	-0.009***	0.003	0.002*	0.002	0.001
	(0.000)	(0.003)	(0.001)	(0.002)	(0.002)
Power Plant FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	764594	764594	764594	577379	577379

Note: This Table shows DiD estimation results for the election of Donald Trump as President in the end of 2016 according to eq. (1). The dependent variable is a power plants probability of being constructed in a sample of green power plants. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.5 Robustness

Our results are robust to different sampling choices, to different empirical specifications and to a permutation test. First, to assess whether the treatment effect could arise by chance under random treatment assignment, we implement a randomization-inference (permutation) test. We therefore repeatedly reassign the treatment indicator across countries (holding the panel structure fixed) and re-estimate the full DiD specification in each draw, recording the placebo treatment coefficient. Results are provided in table 17 and fig. 11 and show at the 5% significance level, that the observed DiD estimate for a brown asset sale from a foreign-liberal to a home investor is 0.1067 based on 163 permutations. The randomization-inference two-sided p-value equals 0.0123, indicating that the estimated effect is unlikely to be generated by chance. Second, we leverage the vast number of observations in the control countries and 1:1 match treated and control samples by means of coarsened exact matching (Blackwell et al., 2009). As reported in table 18, we successfully match power plants based on MW, plant age, ownership and fuel type. We can thereby address concerns related to different compositions of the power plant fleet in the US and the control countries, which might explain our findings. Results for the probabilities of home-foreign transaction are reported in table 19 and indicate roughly comparable significant results: home asset owners are more likely to buy brown power plants from foreign investors, while foreign investors are less likely to buy from home investors. This effect is more than 3x stronger for foreign-liberal- compared to foreign-conservative investors. Third, a potential concern is that some non-OECD control countries are not comparable to the US due to for example less developed capital markets. We therefore re-run eq. (1) for the asset transaction between foreign and home investors in a sample of OECD power plants. Results for the reduced sample in table 20 show comparable results to our baseline findings in table 5. Fourth, one could also question the validity of the LLM categorization which is particularly relevant for the classification of investor countries. We therefore re-run eq. (1) in a reduced sample that does not rely on any LLM categorization for both ownership type and investor country. Results in table 21 show comparable results to our baseline finding. Fifths, we re-run the did model in a full sample, that does not exclude investors from countries that experienced political shocks. Results in table 22 show a strong positive treatment effect for home purchases from foreign investors. Finally, we change the empirical specification and re-run eq. (1) without MW-weighting the observations. Results in table 23 show a substantially reduced treatment effect for the brown asset sale from foreign to home investors, however, the coefficient estimate is still highly significant and positive. Reduced coefficient estimates can be expected given that the unweighted estimation introduces a lot of noise from very small asset transactions.

4.6 The effect of right-wing populist elections on power plant ownership

We extend the study towards all right-wing populist elections in our time frame. We therefore leverage the comprehensive list of populist election victories by Funke et al., 2023. Beyond the election of Donald Trump in the US, there are seven additional right-wing populist election shocks between 2011 and 2021, that is, in Brazil, Bulgaria, India, Italy, the Philippines, the United Kingdom, and Poland. We estimate the effect of right-wing populist elections on power plant ownership using a stacked difference-in-differences design (Cengiz et al., 2019; Baker et al., 2022) to avoid negative weighting when using standard two-way fixed effects estimators in the presence of heterogeneous or dynamic treatment effects (Goodman-Bacon, 2021). For each treatment cohort c, defined by the year E_c, we construct a cohort-specific dataset containing all plants in treated countries and a set of "clean" control countries that remain untreated throughout the event window $[E_c-K, E_c+K]$. These cohort-specific datasets are then appended into a single stacked panel. We estimate the following empirical specification:

$$Y_{ist} = \beta_0 + \beta_1 \Big(\text{Post}_{st} \times \text{Treat}_i\Big) + \gamma_{is} + \delta_{st} + \varepsilon_{ist}, \tag{3}$$

where Y_{ist} is the probability of plant i in stack s and year t to be sold or purchased. $\text{Post}_{st} \times \text{Treat}_i$ is an indicator equal to one for plants in treated countries in post-treatment years within the stack-specific window, γ_{is} are power plant-by-stack fixed effects, and δ_{st} are year-by-stack fixed effects that absorb common shocks within each stack. The coefficient β_1 captures the average treatment effect on treated plants over the post-treatment window. We cluster standard errors at the country level to reflect the national treatment assignment and to account for dependence across plants and across stacks within countries.

Results for the dynamic stacked DiD estimation with 3-year windows are reported in fig. 4 and show that the main results for the US holds for other right-wing populist election shocks: foreign liberal investors sell brown power plants to home investors after right-wing populist leaders are newly elected. The dynamic yearly coefficient estimates amount to almost 10 percentage points for the two years following a newly elected right-wing populist leader.

In table 8, we extend the analysis to home-foreign transactions. The propensity of a foreign investor owned brown power plant to be sold to a home investor is marginally significant and positive, albeit with a smaller coefficient compared to the US results. The coefficient estimate for foreign conservative investors selling to home investors is not significant, but the coefficient for foreign liberal investors is highly significant and economically meaningful with almost 7 percentage points.

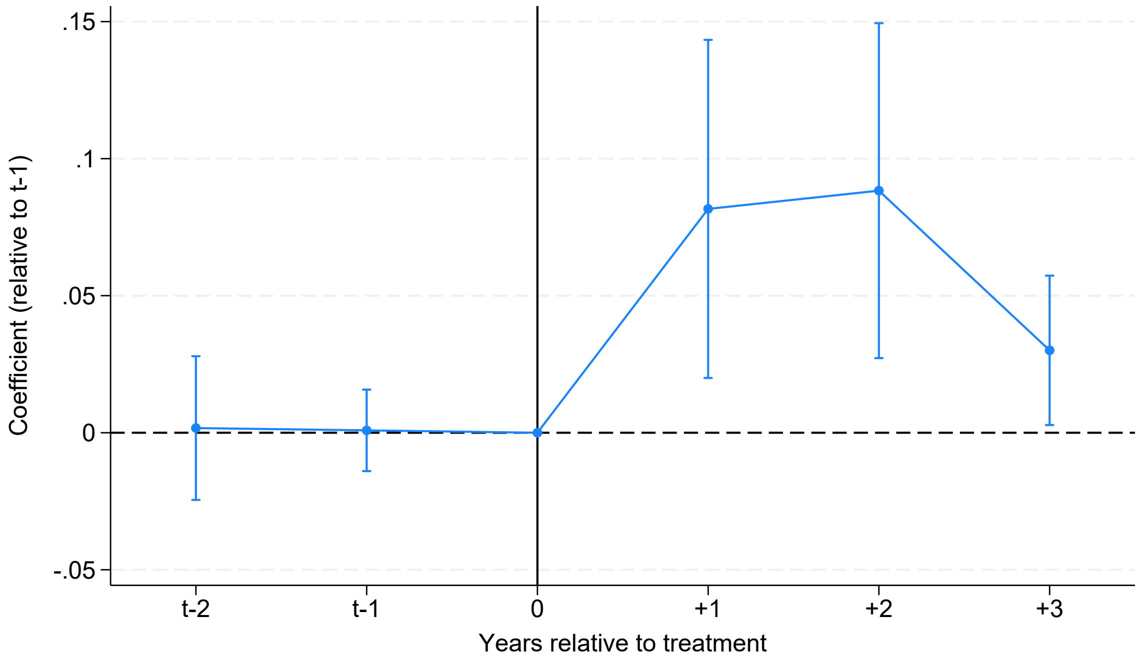

Figure 4: Event study figure for the stacked DiD estimation for brown power plants. The dependent variable is a brown power plants probability of being sold by a foreign-liberal parent to a home asset owner. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021. We use 3-year stacked estimation windows for treated countries. Standard errors are clustered at the country level.

Overall, the stacked DiD results mirror the US results, albeit with smaller coefficient estimates. We therefore conclude that right-wing populist elections seem to scare off foreign investors, particularly foreign-liberal investors, who are politically less aligned with the new right-wing populist agenda. Home investors of populist countries invest in brown capacity and buy power plants from foreign asset owners.

Table 8: Effect of right-wing populist elections on brown power plant ownership: Asset transaction between home and foreign parents

	(1) Foreign→home	(2) Home→foreign	(3) Foreign-con.→home	(4) Foreign-lib.→home
US*Post	0.040*	-0.003	0.041	0.068***
	(0.024)	(0.004)	(0.045)	(0.020)
Power Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	532241	1529498	186638	231792

Note: This Table shows DiD estimation results for the election of right-wing populist leaders between 2011 and 2021 according to eq. (3). The dependent variable is a brown power plants probability of being sold by a specific parent to a new specific parent. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021. We use 3-year stacked estimation windows for treated countries. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Discussion & conclusion

Summing up, we study detailed ownership dynamics in the US power plant sector over time. We leverage our unique dataset to analyze the impact of the Trump election shock on US power plant ownership compared to an international control group. We find strong evidence that the Trump election shock significantly affected brown and green power plant sales, purchases, new constructions and decommissionings: Home investors increase the purchase of brown power plants, while foreign investors are more likely to sell brown power plants but to buy green power plants. We also provide new evidence that this effect persists outside the US for other countries with right-wing populist election shocks. In line with Hypothesis 1, we explain these results with an increasing uncertainty for foreign investors in the US as Trump favored domestic ownership of strategic long-lived assets. However, as stipulated in Hypotheses 2-3, this effect is moderated by both political alignment as well as climate alignment of the different investor groups: Brown divestment is stronger for foreign-liberal investors and home-investors only increase the purchases of brown, but not green power plants.

Hence, our results indicate that the purchasing or sale decision of a parent is shaped by the interaction of the political distance of the respective investor and the climate preferences of the respective power plant owner. Most notably, home investors are most aligned with the new political orientation of the US. Foreign-conservative investors are politically more aligned to the new US ideology, compared to foreign-liberal investors. This political distance is closely mirrored by the purchase dynamics of power plants. While, home investors increase purchases, foreign-liberal investors strongly sell power plants to reduce the uncertain US exposure. However, this effect is moderated by the power plants transition risk, as foreign-liberal investors actually increase the purchases of green power plants, while they reduce brown purchases. Home-listed investors on the other hand increase brown purchases but reduce new green constructions. We rationalize this pattern by changing preferences of home-investors compared to foreign investors. US investors seem to adopt the pro-fossil fuel preferences of the US president, while foreign-liberal investors are investing against the backdrop of increasingly stringent and ambitious climate policies at home. Examples include the Paris Agreement or the EU Green Deal. Our results are in line with previous research (Berg et al., 2023), which shows that listed EU owners divest from pollutive assets after the Paris Agreement. We show opposite results for US listed owners as a reaction to the Trump election shock.

Future research could test left/socialist political shocks in other jurisdictions to better understand how right- and left-wing political shocks differ in terms of ownership changes. Studies could also include the transaction value of the power plant sales to learn whether political shocks affect the value of power plants.

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6 Appendix

6.1 Asset ownership flows in the US

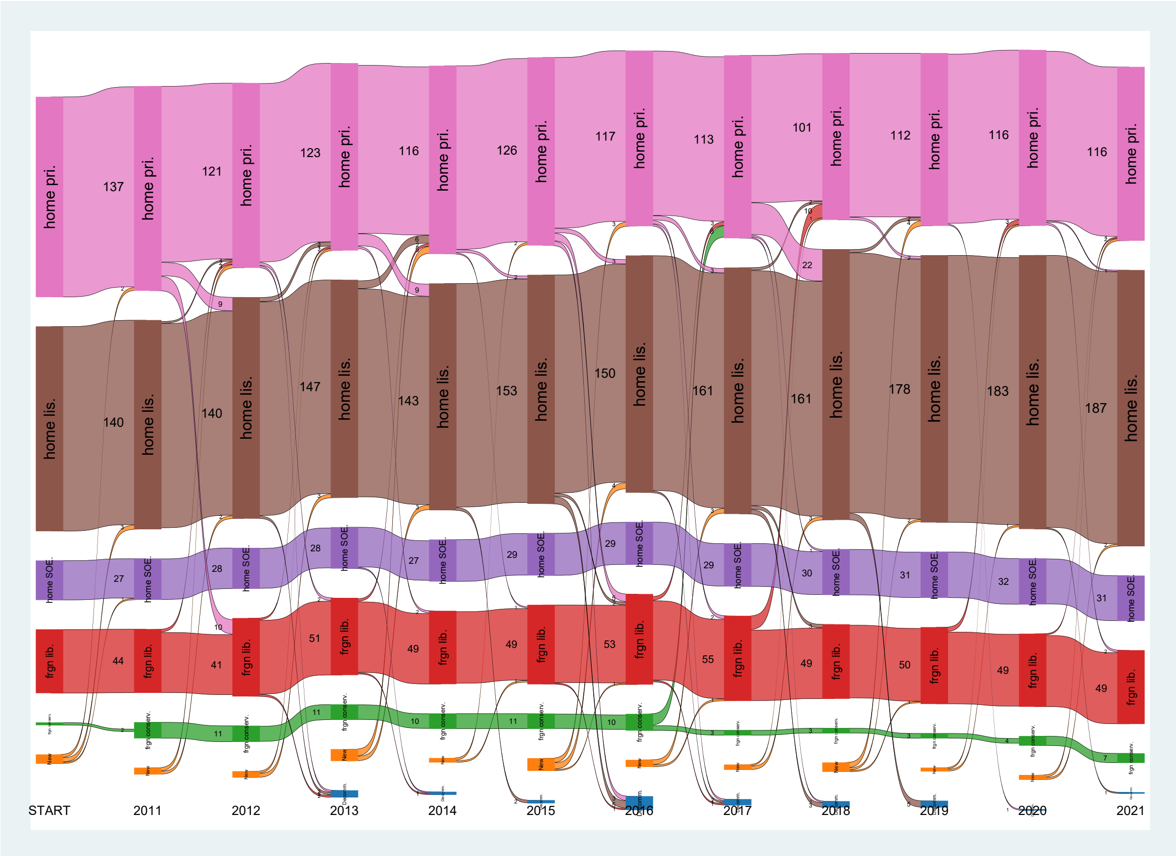

Figure 5: Flow diagram for gas power plants in the US from 2011 until 2021. The numbers in the figure indicate GW held by the respective owner. Asset flows below 1 GW are excluded for readability.

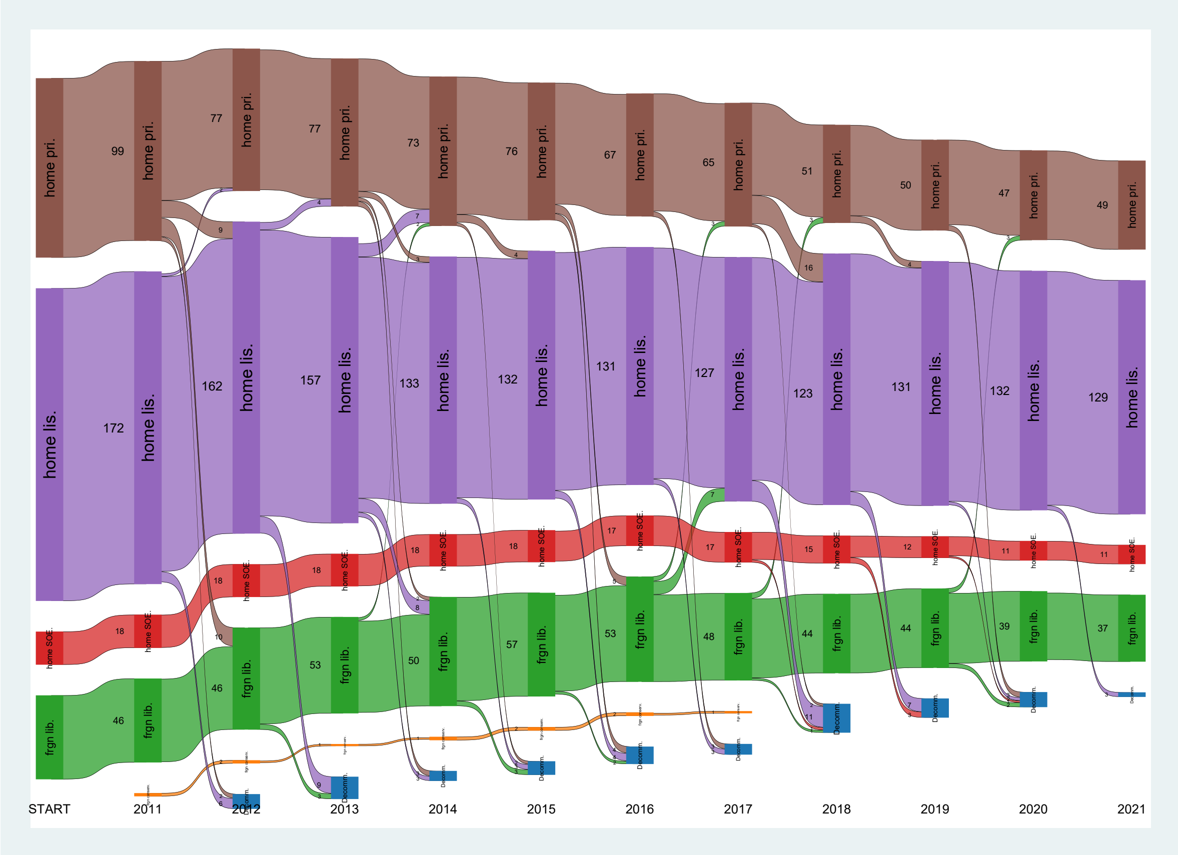

Figure 6: Flow diagram for coal power plants in the US from 2011 until 2021. The numbers in the figure indicate GW held by the respective owner. Asset flows below 1 GW are excluded for readability.

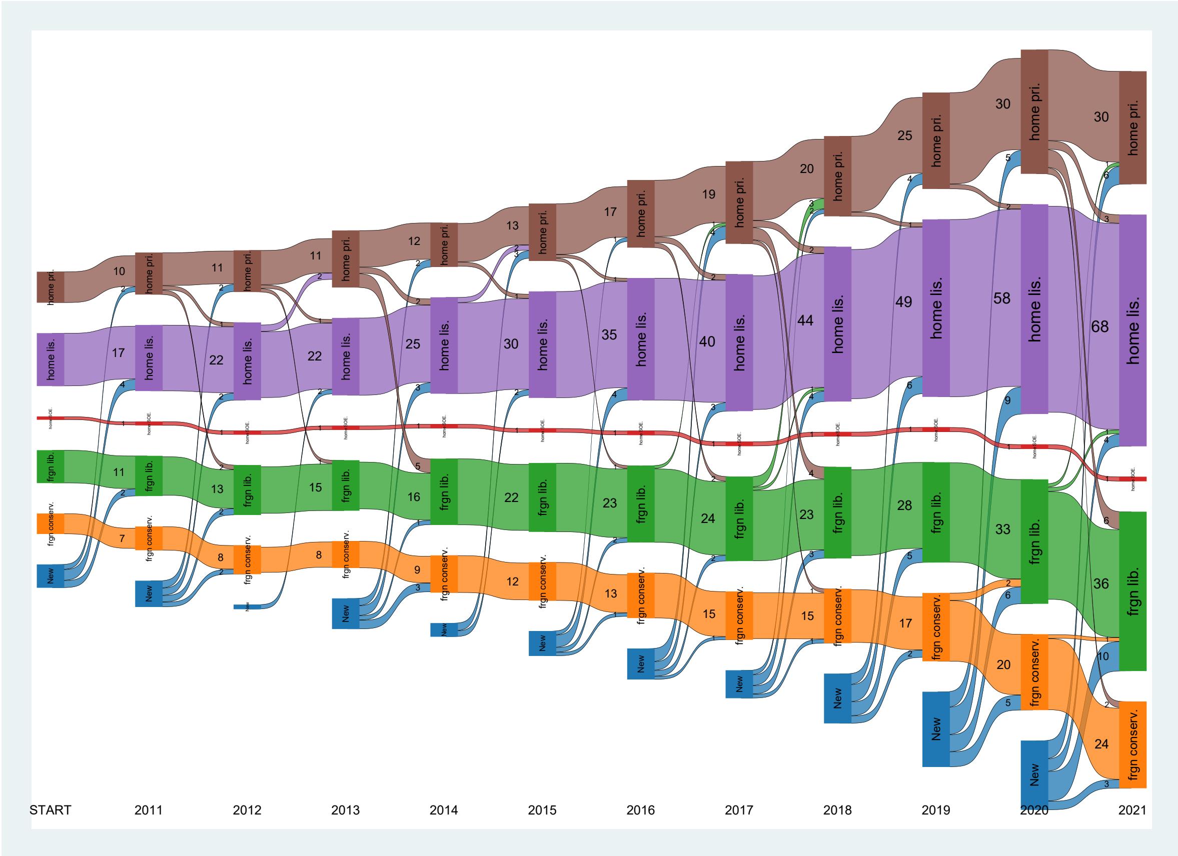

Figure 7: Fflow diagram for renewable power plants in the US from 2011 until 2021. The numbers in the figure indicate GW held by the respective owner. Asset flows below 1 GW are excluded for readability.

6.2 The effect of the Trump election on brown power plant ownership

Table 9: Effect of the 2016 US presidential election on brown power plant ownership by investor group

	(1) Home-listed	(2) Home-private	(3) Home-SOE	(4) Foreign-conservative	(5) Foreign-liberal
Panel A: Sales by investor group					
US*Post	-0.005 (0.012)	0.071*** (0.012)	0.035*** (0.008)	0.063*** (0.010)	0.119*** (0.008)
Power Plant FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	85873	261985	140785	47845	66319
Panel B: Purchases by investor group					
US*Post	0.007*** (0.001)	0.023*** (0.004)	0.009*** (0.002)	0.008** (0.003)	-0.007 (0.005)
Power Plant FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	726761	726761	726761	471253	471253
Panel C: Decommissionings by investor group					
US*Post	0.000 (0.005)	0.007* (0.004)	0.027*** (0.003)	0.004 (0.004)	-0.000 (0.007)
Power Plant FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	97363	294520	157849	54322	75612

Note: This table shows DiD estimation results for the election of Donald Trump as President at the end of 2016 according to eq. (1). In panel A, the dependent variable is a brown power plant's probability of being *sold* by a specific investor group. In panel B, the dependent variable is a brown power plant's probability of being *bought* by a specific new parent. In panel C, the dependent variable is a brown power plant's probability of being *decommissioned* by a specific parent. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

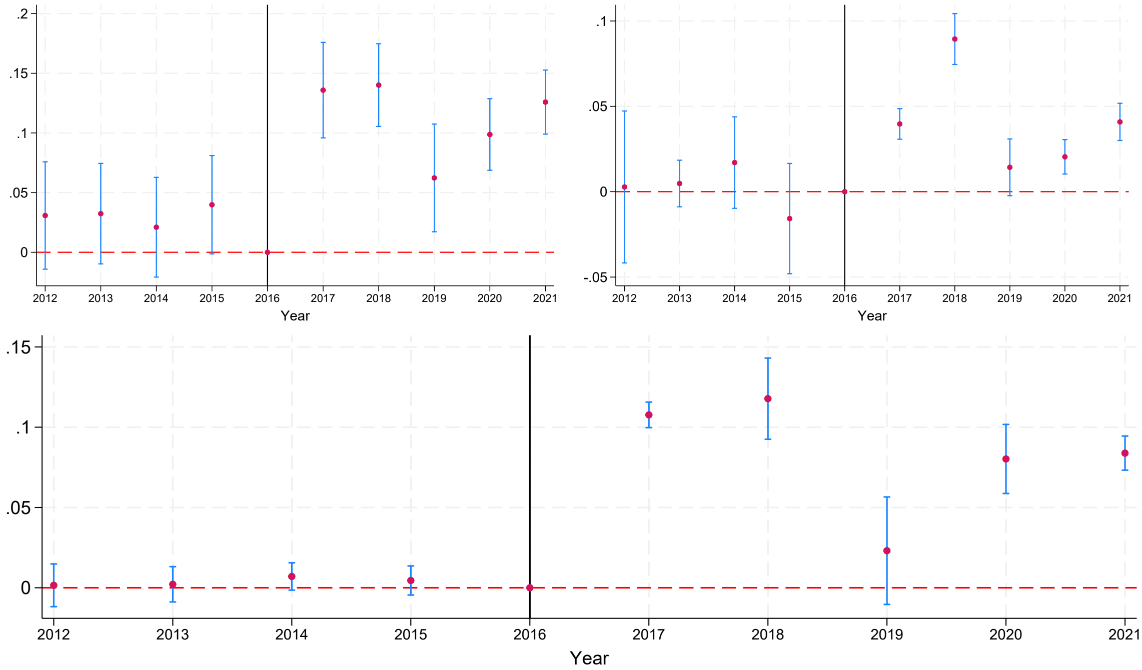

Figure 8: Summary event study figure of the election of Donald Trump as President in the end of 2016 for brown power plants. The dependent variable is a brown power plants probability of being sold by a foreign parent in the top-left panel. It is a brown power plants probability of being purchased by a home parent in the top-right panel. The bottom panel shows the treatment effect probability of a brown power plant that is sold by a foreign investor to a home asset owner. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors are clustered at the country level.

6.3 The effect of the Trump election on brown power plant trading: All asset transactions

Table 10: Effect of the 2016 US presidential election on power plant ownership: All brown power plant transitions between different asset owner groups.

Panel A: Home-listed investors buys brown power plant from: →				
	Home-private	Home-SOE	Foreign-conservative	Foreign-liberal
did	0.048***	-0.001*	-0.005	0.040***
	(0.002)	(0.000)	(0.004)	(0.003)
Observations	261,985	140,785	47,845	66,319
Panel B: Home-private investors buys brown power plant from: →				
	Home-listed	Home-SOE	Foreign-conservative	Foreign-liberal
did	-0.004***	-0.002	0.072***	0.066***
	(0.001)	(0.002)	(0.003)	(0.003)
Observations	85,873	140,785	47,845	66,319
Panel C: Home-SOE investors buys brown power plant from: →				
	Home-listed	Home-private	Foreign-conservative	Foreign-liberal
did	-0.000	0.004	0.011***	0.000
	(0.000)	(0.004)	(0.000)	(0.002)
Observations	85,873	261,985	47,845	66,319
Panel D: Foreign-conservative investors buys brown power plant from: →				
	Home-listed	Home-private	Home-SOE	Foreign-liberal
did	-0.001	-0.002**	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.002)
Observations	70,204	169,268	62,227	66,319
Panel E: Foreign-liberal investors buys brown power plant from: →				
	Home-listed	Home-private	Home-SOE	Foreign-conservative
did	-0.015	-0.023***	-0.002	-0.030**
	(0.012)	(0.003)	(0.001)	(0.011)
Observations	70,204	169,268	62,227	47,845

Note: This Table shows DiD estimation results for the election of Donald Trump as President in the end of 2016 according to eq. (1) for all buyer - seller combinations. The dependent variable is a brown power plants probability of being traded by the respective buyer and seller. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.4 The effect of the Trump election on gas power plant ownership

Table 11: Effect of the 2016 US presidential election on gas power plant ownership: Sales by investor group

	(1) Home-listed sale	(2) Home-private sale	(3) Home-SOE sale	(4) Foreign-conservative sale	(5) Foreign-liberal sale
US*Post	-0.023**	0.069***	0.014	-0.026**	0.110***
	(0.010)	(0.015)	(0.014)	(0.012)	(0.004)
Power Plant FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	46439	128204	54899	25866	38126

Note: This Table shows DiD estimation results for the election of Donald Trump as President in the end of 2016 according to eq. (1). The dependent variable is a gas power plants probability of being sold by a specific parent. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Effect of the 2016 US presidential election on gas power plant ownership: Purchases by investor group

	(1) Home-listed purchase	(2) Home-private purchase	(3) Home-SOE purchase	(4) Foreign-conservative purchase	(5) Foreign-liberal purchase
US*Post	0.000	0.022***	0.010**	0.012**	-0.007
	(0.002)	(0.004)	(0.004)	(0.006)	(0.007)
Power Plant FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	347993	347993	347993	279202	279202

Note: This Table shows DiD estimation results for the election of Donald Trump as President in the end of 2016 according to eq. (1). The dependent variable is a gas power plants probability of being bought by a specific new parent. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Effect of the 2016 US presidential election on gas power plant ownership: Asset transaction between home and foreign parents

	(1) Foreign→home	(2) Home→foreign	(3) Foreign-con.→home	(4) Foreign-lib.→home
US*Post	0.075***	-0.013***	0.004	0.107***
	(0.009)	(0.005)	(0.007)	(0.004)
Power Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	78161	230106	25866	38126

Note: This Table shows DiD estimation results for the election of Donald Trump as President in the end of 2016 according to eq. (1). The dependent variable is a gas power plants probability of being sold by a specific parent to a new specific parent. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

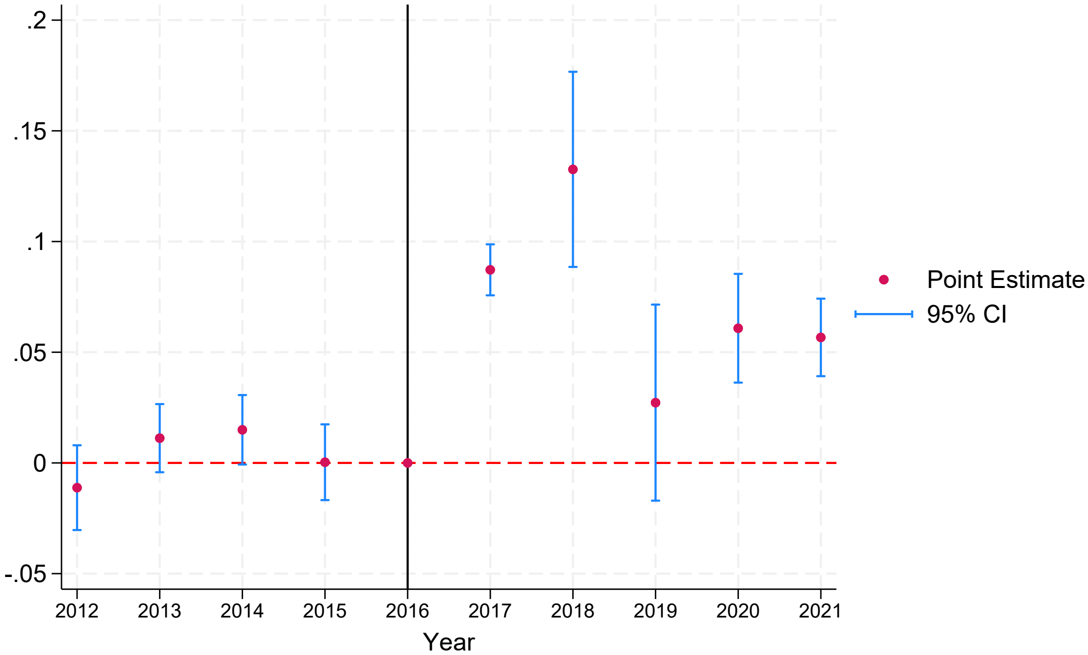

Figure 9: Event study figure of the election of Donald Trump as President in the end of 2016. The dependent variable is a gas power plants probability of being sold from a foreign parent to a home parent. The unit of observation is the yearly MW-weighted power-plant level. The sample period is the full years 2011 to 2021. Standard errors are clustered at the country level.

6.5 The effect of the Trump election on coal power plant ownership

Table 14: Effect of the 2016 US presidential election on coal power plant ownership: Sales by investor group

	(1) Home-listed sale	(2) Home-private sale	(3) Home-SOE sale	(4) Foreign-conservative sale	(5) Foreign-liberal sale
US*Post	0.008 (0.021)	0.081*** (0.012)	0.039*** (0.006)	0.182*** (0.007)	0.122*** (0.020)
Power Plant FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	13781	36735	16132	5505	7514

Note: This Table shows DiD estimation results for the election of Donald Trump as President in the end of 2016 according to eq. (1). The dependent variable is a coal power plants probability of being sold by a specific parent. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Effect of the 2016 US presidential election on coal power plant ownership: Purchases by investor group

	(1) Home-listed purchase	(2) Home-private purchase	(3) Home-SOE purchase	(4) Foreign-conservative purchase	(5) Foreign-liberal purchase
US*Post	0.017***	0.017***	0.009***	0.005***	-0.006
	(0.002)	(0.005)	(0.002)	(0.002)	(0.004)
Power Plant FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	99226	99226	99226	43254	43254

Note: This Table shows DiD estimation results for the election of Donald Trump as President in the end of 2016 according to eq. (1). The dependent variable is a coal power plants probability of being bought by a specific new parent. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Effect of the 2016 US presidential election on coal power plant ownership: Asset transaction between home and foreign parents

	(1) Foreign→home	(2) Home→foreign	(3) Foreign-con.→home	(4) Foreign-lib.→home
US*Post	0.083***	-0.011***	0.179***	0.095***
	(0.006)	(0.003)	(0.005)	(0.009)
Power Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	20564	66858	5505	7514

Note: This Table shows DiD estimation results for the election of Donald Trump as President in the end of 2016 according to eq. (1). The dependent variable is a coal power plants probability of being sold by a specific parent to a new specific parent. The unit of observation is the MW-weighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

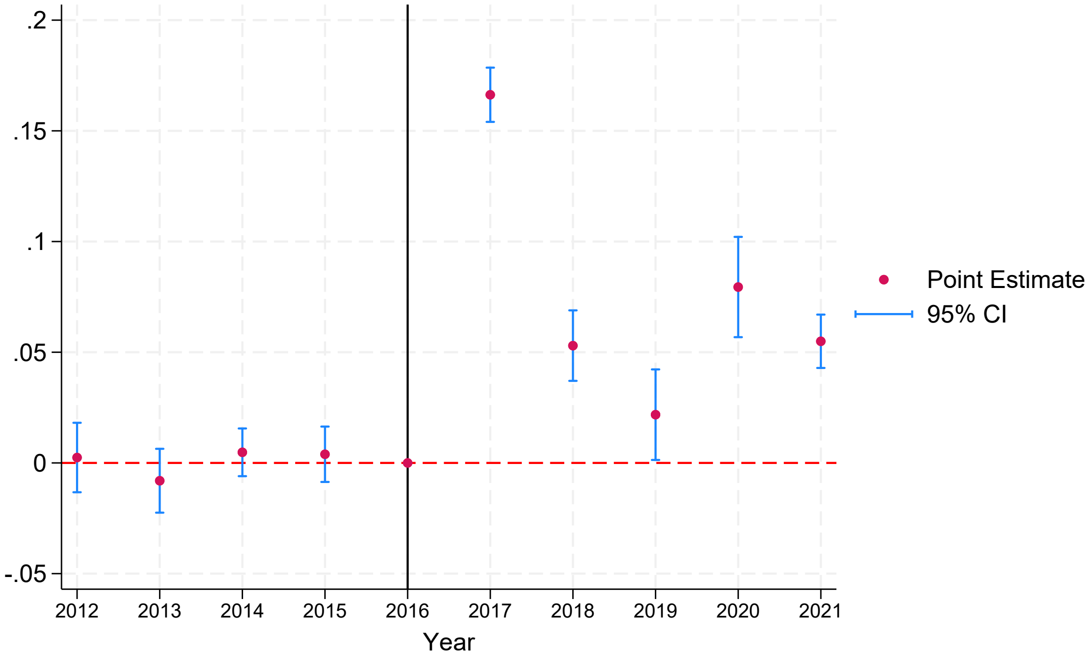

Figure 10: Event study figure of the election of Donald Trump as President in the end of 2016. The dependent variable is a coal power plants probability of being sold from a foreign parent to a home parent. The unit of observation is the yearly MW-weighted power-plant level. The sample period is the full years 2011 to 2021. Standard errors are clustered at the country level.

6.6 Robustness

Table 17: Randomization Inference (Permutation) Test

Statistic	Value
Observed DiD estimate	0.1067
Two-sided RI p-value	0.0123
Number of permutations used	163

Note: This table reports the two-sided p-value from a randomization-inference (permutation) test based on 163 permutations of the treatment assignment under the sharp null of no treatment effect. The observed statistic is the difference-in-differences estimate. The dependent variable is a brown power plants probability of being sold by a foreign liberal investor to a home investor.

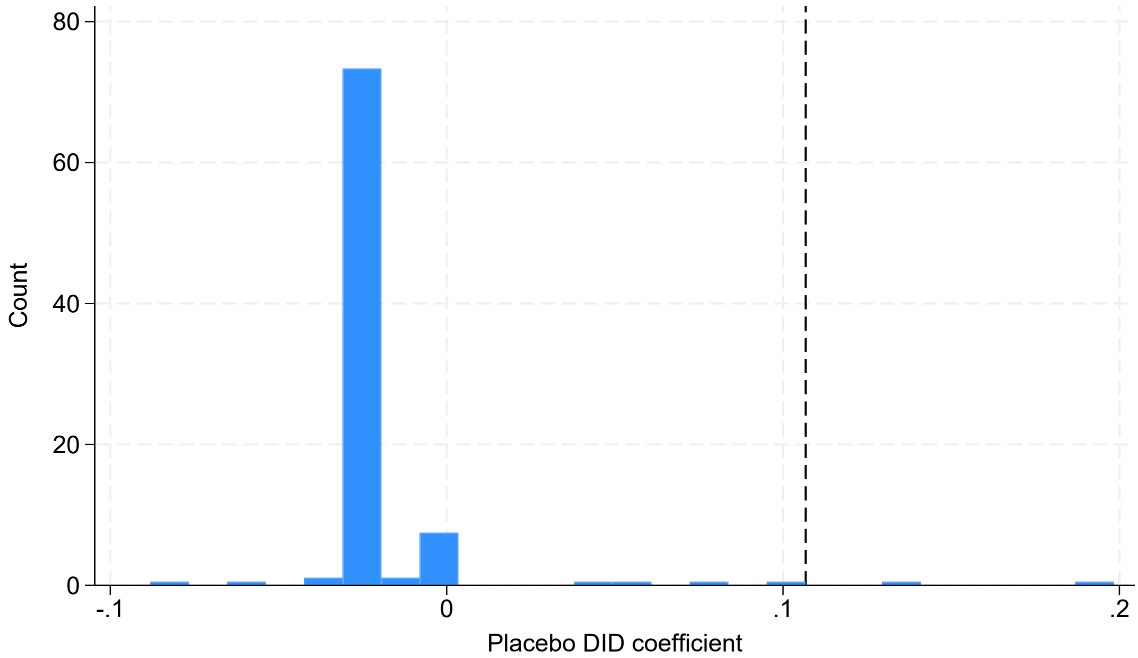

Figure 11: This figures displays the results for the two-sided randomization-inference (permutation) test based on 163 permutations of the treatment assignment under the sharp null of no treatment effect. The dependent variable is a brown power plants probability of being sold by a foreign liberal investor to a home investor. The observed statistic is the difference-in-differences estimate.

Table 18: Covariate balance before and after matching

	Before matching				After matching			
	Control		Treated		Control		Treated	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Ownership status	2.519	0.707	2.335	0.768	2.402	0.754	2.402	0.754
Capacity (MW)	25.56	92.48	53.36	133.77	27.78	86.43	33.29	87.55
Plant age	24.77	23.14	27.98	24.66	27.29	25.12	27.44	25.22
Fuel type	42.00	15.96	36.56	16.00	38.16	15.80	38.20	15.82
Std. diff. (Ownership)	0.250				0.000			
Std. diff. (MW)	-0.242				-0.063			
Std. diff. (Plant age)	-0.134				-0.006			
Std. diff. (Fuel)	0.341				-0.003			

Note: The table reports means and standard deviations for treated and control power plants before and after matching. Standardized differences are reported to assess covariate balance; values below 0.1 are generally considered indicative of good balance.

Table 19: Effect of the 2016 US presidential election on power plant ownership: Asset transaction between home and foreign parents - brown power plants in a 1:1 matched sample

	(1) Foreign→home	(2) Home→foreign	(3) Foreign-con.→home	(4) Foreign-lib.→home
US*Post	0.070***	-0.016***	0.025**	0.090***
	(0.006)	(0.006)	(0.010)	(0.003)
Power Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	51657	182295	14827	27627

Note: This Table shows DiD estimation results for the election of Donald Trump as President in the end of 2016 according to eq. (1) in a 1:1 matched sample. The dependent variable is a brown power plants probability of being sold by a specific parent to a new specific parent. The unit of observation is the unweighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 20: Effect of the 2016 US presidential election on power plant ownership: Asset transaction between home and foreign parents - brown power plants in OECD countries

	(1) Foreign→home	(2) Home→foreign	(3) Foreign-con.→home	(4) Foreign-lib.→home
US*Post	0.078***	-0.018**	0.084***	0.102***
	(0.015)	(0.007)	(0.001)	(0.008)
Power Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	73891	268699	25544	38018

Note: This Table shows DiD estimation results for the election of Donald Trump as President in the end of 2016 according to eq. (1) in a sample of OECD power plants. The dependent variable is a brown power plants probability of being sold by a specific parent to a new specific parent. The unit of observation is the unweighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 21: Effect of the 2016 US presidential election on power plant ownership: Asset transaction between home and foreign parents - brown power plants without LLM categorization

	(1) Foreign→home	(2) Home→foreign	(3) Foreign-con.→home	(4) Foreign-lib.→home
US*Post	0.069***	-0.009***	0.060***	0.085***
	(0.005)	(0.002)	(0.001)	(0.004)
Power Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	127163	269934	39533	54554

Note: This Table shows DiD estimation results for the election of Donald Trump as President in the end of 2016 according to eq. (1) in a sample without any LLM classified observations. The dependent variable is a brown power plants probability of being sold by a specific parent to a new specific parent. The unit of observation is the unweighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 22: Effect of the 2016 US presidential election on power plant ownership: Asset transaction between home and foreign parents - brown power plants in all countries

	(1) Foreign→home	(2) Home→foreign	(3) Foreign-con.→home	(4) Foreign-lib.→home
US*Post	0.093*** (0.006)	-0.012*** (0.003)	0.319*** (0.007)	0.099*** (0.003)
Power Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	178578	522153	61901	76826

Note: This Table shows DiD estimation results for the election of Donald Trump as President in the end of 2016 according to eq. (1) in a full sample that is not constrained by the exclusion of investors from countries that experienced political shocks after 2016. The dependent variable is a brown power plants probability of being sold by a specific parent to a new specific parent. The unit of observation is the unweighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 23: Effect of the 2016 US presidential election on power plant ownership: Unweighted asset transaction between home and foreign parents - brown power plants

	(1) Foreign→home	(2) Home→foreign	(3) Foreign-con.→home	(4) Foreign-lib.→home
US*Post	0.031***	-0.002	0.031***	0.041***
	(0.004)	(0.004)	(0.007)	(0.003)
Power Plant FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	153134	489769	47845	66319

Note: This Table shows DiD estimation results for the election of Donald Trump as President in the end of 2016 according to eq. (1). The dependent variable is a brown power plants probability of being sold by a specific parent to a new specific parent. The unit of observation is the unweighted yearly power-plant level. The sample period is the full years 2011 to 2021. Standard errors in parentheses are clustered at the country level. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.7 Descriptive statistics

Table 24: Parent ownership distribution

	Frequency	**Percent**
Private company listed	398,025	21.55
Private company unlisted	1,050,021	56.86
State Owned Enterprise	398,590	21.58
Total	1,846,636	100.00

Note: This tables shows the ownership classification of the parents across three dimensions: listed, unlisted, and SOE.

Table 25: Parent geographic information

	Frequency	**Percent**
Europe	795,815	41.19
Asia	545,466	28.23
North America	388,042	20.09
ROW	208,505	10.79
Total	1,931,937	100.00

Note: This tables shows the geographic classification of the parents across continents.

6.8 Prompt for ChatGPT o4-mini-high for aligning parent names

We use the following prompt to align similar parents:

"I will provide you with a list of companies. Check whether there are any duplicates, i.e., companies which merely changed names, or a only written slightly different, or changed legal form, or only subsidiaries of a same parent from the list. If that's the case rename the company (with stata coding) so that both company names are exactly aligned. Do this for every company of the list. For subsidiaries, keep the name of the parent. Return only stata code, no comments . The variable is called PARENT. You can also rely on the companies I already provided.

Next do it for this list of companies: "

6.9 Prompt for ChatGPT o4-mini-high and DeepSeek-V3: Detecting ownership information

We use the following prompt to gather both location as well as ownership type:

"I am going to provide you with a list of companies. Can you return in tabulated form for every company of that list: The company name (similar spelling), the country of the headquarter of the company, the legal form (private company unlisted, private company listed, majority state owned company)

Only provide one option for each field, only use the exact words i provided! Do not invent answers, only answer when you are certain, if not certain, leave the info blank but still return the company name. Use information from: your training set and general knowledge, but also rely on information from the company name directly (the language of the name, location information in name, legal form of company (plc, inc, gmbh) etc.) List:"