Royal Holloway, University of London

PR5430: DPG Dissertation

From Climate Ambition to Security Imperative: Russian Gas Dependence and Post-2022 Renewable Generation in the EU

Course Title: MSc International Relations

Supervisor: Dr Janina Beiser-McGrath

Candidate Number: 2404086

Word Count: 11896

Contents

Abstracts

Climate urgency built targets but delivered gradualism; Russia's invasion reframed renewables as security assets and accelerated action. This study tests whether that frame translated into measurable increases in renewable generation across EU member states, and whether gains scale with pre-war Russian gas dependence. Using monthly and quarterly data, the analysis triangulates across four designs: a continuous-treatment difference-in-differences, a dynamic event-time specification, a categorical exposure model, and a Callaway–Sant'Anna cohort estimator, with a Green Deal–timed placebo. Results are coherent across designs: pre-trends are flat, post-2022 paths turn upward, and effects are larger in earlier, more exposed cohorts, while large systems with mid-range exposure show modest share shifts but substantial level additions. The pattern fits a practice view of securitisation in which empowered audiences convert a security frame into auctions, expedited permitting, and deployment. Findings support a security-driven acceleration rather than policy drift, clarify scope conditions, and link securitisation theory to observable system change.

1.1 Introduction

Europe's energy transition offers a puzzle. Climate-framed governance produced targets and plans, yet change often moved at an incremental tempo shaped by permitting, grids, and routine trade-offs. After Russia's invasion, the same technologies were recast as security assets. This paper treats that shift as a securitising move whose effects depend on audiences and institutions, not slogans alone. Securitisation theory explains how issues are lifted into a register of existential threat and emergency measures when receptive, empowered audiences can authorise and implement extraordinary action, a practice perspective that travels well to energy policy (Buzan, Wæver and de Wilde; Balzacq; Balzacq, Léonard and Ruzicka). Sectoral work on the war's energy politics shows why the frame resonated: Russia-related gas dependencies created structural exposure that constrained substitution while sharpening incentives once the shock bound, and policy assessments documented an immediate tightening of EU ambition and instruments. Public opinion provided permissive consensus. Together, these strands motivate the core question this study asks about a security-driven acceleration in renewable generation and its cross-national variation.

The post-invasion policy turn was not only rhetorical; it re-specified instruments and timelines in ways that plausibly change near-term outcomes. REPowerEU framed renewables, efficiency and diversification as tools of strategic autonomy, calling for a "massive speed-up and scale-up of renewable energy" in order to "rapidly reduce our dependence on Russian fossil fuels by fast-forwarding the clean transition" (European Commission, 2022). The follow-through embedded speed in law: the revised Renewable Energy Directive set a binding 2030 objective of "at least 42.5%… aiming for 45%," and the Emergency Regulation on permitting instructed authorities to treat renewables as an "overriding public interest," compressing deadlines and simplifying procedures (European Commission, 2023a; European Commission, 2023b). Contemporary assessments linked Europe's upgraded trajectories to this security-centred package rather than routine target revision, while sectoral analyses traced why the frame resonated in systems where pipelines, contracts and grid constraints created structural exposure (IEA, 2022; Kuzemko et al., 2022; Sharples, 2020). In short, the war supplied a focusing event, policy supplied exceptional instruments, and audiences supplied legitimacy—together furnishing a theory-ready context for testing whether acceleration is observable in the data (Balzacq, 2005; Balzacq, Léonard and Ruzicka, 2016; Buzan, Wæver and de Wilde, 1998).

Against this backdrop, this study asks a simple question with theoretical bite: did the securitisation of energy policy after Russia's invasion catalyse an observable acceleration in renewable generation across EU member states, and did the intensity of this acceleration vary with pre-war Russian gas dependence. The expectation follows from practice-oriented securitisation theory, which holds that emergency claims translate into outcomes when receptive and empowered audiences can authorise and implement extraordinary measures, not when slogans circulate in the abstract (Buzan, Wæver and de Wilde, 1998; Balzacq, 2005; Balzacq, Léonard and Ruzicka, 2016). It also follows from sectoral work showing how structural dependence, pipeline topology, and contract lock-in both constrain substitution and sharpen incentives once a shock binds, particularly where security of supply is salient in executive and regulatory arenas (Sharples, 2020; Kuzemko et al., 2022; Steffen and Patt, 2022).

The study tests two hypotheses. H1 states that post-invasion acceleration in renewable generation is increasing in pre-war Russian gas dependence, a dose–response consistent with structural exposure and securitised prioritisation. H2 states that when treatment timing is modelled explicitly, earlier and more exposed cohorts exhibit larger post-treatment gains than later or less exposed cohorts, consistent with the claim that what matters is not audience size but which audiences are positioned to validate and enact rapid measures. These hypotheses are evaluated with modern complementary designs that fit the EU setting: a continuous-treatment difference-in-differences to recover dose–response and dynamics, and a cohort estimator for group-time average treatment effects under staggered adoption, following best practice on event-time heterogeneity, composition, and interpretation in DiD applications (Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Callaway, Goodman-Bacon and Sant'Anna, 2025).

The contribution is twofold. Substantively, the paper links securitisation theory to system change by reading EU-level speech acts and legal instruments together with cross-national differences in exposure and timing, showing how security framing can reconfigure pace and sequence in the energy transition. Methodologically, the paper triangulates across designs rather than leaning on a single specification, pairs continuous-treatment estimates with cohort effects, and deploys an event-time placebo aligned with the Green Deal timing to separate a security-shock story from policy drift. This approach engages recent debates on identification in staggered settings while keeping the estimands close to the policy question (Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Callaway, Goodman-Bacon and Sant'Anna, 2025).

The article proceeds in five steps. The theoretical framework and literature review situates the argument in securitisation as practice, emphasising audience configuration and institutional capacity. The methodology specifies the data and identification strategy, including continuous-treatment and cohort designs and the placebo. The analysis presents descriptives, main estimates, dynamics, robustness, and the placebo contrast, and then relates the pattern to policy texts and public opinion evidence from REPowerEU, RED III, and Eurobarometer and EIB surveys that document audience acceptance of rapid measures (European Commission, 2022; European Commission, 2023a; European Commission, 2023b; EIB, 2023). The discussion draws out implications for theory and policy, including scope conditions where securitisation is likely to accelerate renewable generation. The conclusion summarises the findings and reflects on how security frames can convert climate ambition into near-term deployment in European energy systems. Basically, I question myself if did a war manage to do for climate change what pure conscious couldn't?

2.1 Theoretical Framework - Securitisation and Policy Inertia

Securitisation theory can provide the foundation for understanding how climate and energy policy can be elevated from routine governance into the sphere of urgent and exceptional politics. The Copenhagen School conceptualised security not as an objective condition but as a social construction, enacted when political actors frame an issue as an existential threat that legitimises extraordinary measures (Buzan, Wæver and de Wilde, 1998). This move shifted attention from the material presence of threats to the discursive and institutional processes through which they become recognised as such. Subsequent contributions have refined this framework, stressing that securitisation depends on audience acceptance, cultural resonance, and institutional context, rather than speech acts alone (Balzacq, 2011; Stritzel, 2007; Balzacq, Léonard and Ruzicka, 2016). These insights highlight both the analytical power of securitisation theory and its limitations: critics argue that its emphasis on discourse risks overlooking how entrenched structures and material dependencies constrain political choice (McDonald, 2008; Floyd, 2019). Nevertheless, by explaining how actors can justify exceptional action in response to perceived existential dangers, securitisation theory offers a compelling framework for analysing the politics of climate and energy. It is particularly useful when considered alongside the concept of policy inertia, which helps explain why such exceptional framing may be necessary in the first place.

The mechanism of securitisation rests on the interaction between speech acts, audiences, and institutions. At its core, securitisation theory holds that by declaring an issue to be an existential threat, political actors seek to shift it beyond the realm of normal politics and into the sphere of emergency action (Buzan, Wæver and de Wilde, 1998). Yet subsequent scholars emphasise that such declarations alone are insufficient: securitisation only succeeds when relevant audiences accept the framing and when institutional settings provide channels through which extraordinary measures can be authorised (Balzacq, 2011; Stritzel, 2007). This highlights the relational nature of securitisation, in which political claims resonate to the extent that they align with prevailing fears, cultural narratives, or institutional logics (Balzacq, Léonard and Ruzicka, 2016). The gap between objective and perceived risk illustrates this point: although traffic accidents kill far more people than terrorism, the political framing of terrorism as an existential danger has secured disproportionate attention and resources (McDonald, 2008). In this sense, securitisation is not simply descriptive of material conditions but constitutive of political reality, legitimising extraordinary practices that would otherwise be contested.

A central debate within securitisation theory concerns the normative implications of who is able to define existential threats and the consequences this has for democratic accountability. Floyd (2019) argues that securitisation should not only be analysed as a descriptive process of speech and audience acceptance but also as a normative practice that shapes whose voices count in security politics. In a similar vein, Croft (2011) warns that securitisation can bypass ordinary democratic deliberation, allowing extraordinary measures to be justified without adequate scrutiny. This raises critical questions about authority and legitimacy: while securitisation may galvanise urgent responses, it can also centralise power in the hands of elites and diminish participatory decision-making (Balzacq, 2011; Stritzel, 2007). Such debates underscore the ambivalence of securitisation. On the one hand, framing climate change as an existential threat can draw attention to a problem otherwise neglected by slow-moving institutions. On the other, it risks narrowing the scope of political discussion and excluding alternative voices, thereby trading urgency for democratic breadth.

Over the past two decades, scholarship has traced how climate change has been articulated through a security lens that links environmental disruption to wider vulnerabilities and thereby elevates it on political agendas (Trombetta, 2008; Dalby, 2013). In Europe, this discourse has been reflected institutionally. Analyses of EU foreign and security policy show that climate considerations have been progressively integrated into external action and security thinking, even if not always with consistent priority (Youngs, 2014). The European Commission's European Green Deal further embeds this linkage, presenting the transition as part of a broad strategy to strengthen the Union's economic resilience and competitiveness while coordinating cross-sectoral action (European Commission, 2019). Taken together, these developments indicate that climate politics has moved beyond a purely environmental or moral frame toward one in which risk amplification and systemic exposure are treated as matters for high-level strategic response (Trombetta, 2008; Youngs, 2014). In this sense, climate securitisation has laid a discursive and institutional groundwork through which exceptional measures (accelerated planning, redirected investment, and emergency coordination) can be legitimated when climate-related risks or energy dependencies are perceived to endanger core interests (Dalby, 2013; European Commission, 2019).

While securitisation can elevate climate and energy from routine policy to matters requiring rapid, coordinated response, it also carries significant risks. On the enabling side, arguments for a politics of emergency emphasise that exceptional framing can mobilise resources, compress decision-timelines, and prioritise cross-sectoral coordination that ordinary procedures often fail to deliver (Albert, 2022; European Commission, 2019b). This dovetails with scholarship that traces how linking climate to security has reoriented strategic attention and widened the repertoire of policy instruments available to decision-makers (Dalby, 2013).

At the same time, critical work cautions that the dominant "threat multiplier" framing can narrow climate politics to managerial risk control, align agendas with security institutions' priorities, and displace more transformative or justice-oriented approaches (Cullum, 2024). Normative perspectives further warn that emergency-style responses may centralise authority and reduce opportunities for contestation, raising questions about legitimacy and accountability in how extraordinary measures are defined and implemented (Floyd, 2019). Taken together, these strands suggest that climate securitisation is ambivalent: it can generate momentum to overcome blockage but may also channel action into constrained, security-centric pathways unless explicitly tied to inclusive and transformational goals (Albert, 2022; Cullum, 2024; Dalby, 2013; European Commission, 2019b).

A further obstacle to decisive climate action lies in the persistence of policy inertia. Scholars of institutional change emphasise how established rules, routines, and administrative practices can reproduce the status quo, even in the face of recognised problems (Munck af Rosenschöld, Rozbicka and Lanér, 2014). In the energy domain, this inertia is reinforced by long-lived infrastructures and the structural power of carbon-intensive industries, generating what Unruh (2000) identified as carbon lock-in. Meadowcroft (2011) similarly characterises climate governance under ordinary conditions as incremental and contested, subject to repeated vetoes by actors with entrenched interests. These insights are echoed in research on socio-technical transitions, which shows how path dependence and the agency of incumbent firms constrain the scope for systemic change (Geels, 2014; Kuzemko et al., 2016). Taken together, the literature highlights that climate governance is rarely transformed by gradual reform alone. Instead, inertia tends to perpetuate carbon-intensive trajectories, explaining why extraordinary political framing may be required to break with established routines and enable more disruptive forms of policy intervention.

If climate governance is characterised by inertia, securitisation can be understood as a means of disrupting it. By framing climate or energy dependence as an existential threat, political actors attempt to move the issue beyond incremental negotiation and into the realm of emergency response (Buzan, Wæver and de Wilde, 1998; Balzacq, 2011). Such framing creates the political space to bypass veto players and to accelerate decisions that would otherwise be slowed by entrenched interests (Meadowcroft, 2011). In practice, this may include mobilising large-scale public investment, streamlining permitting procedures, or prioritising renewable deployment as a matter of security rather than economic efficiency. Yet securitisation does not guarantee progressive outcomes. Appeals to energy security have at times reinforced incumbency, legitimising expanded fossil fuel infrastructure instead of structural transition (Bridge et al., 2013; Kuzemko et al., 2016). The relationship between securitisation and inertia is therefore ambivalent: it can provide a window for disruptive change, but the trajectory of that change depends on how exceptional measures are defined and which interests they serve.

A further constraint derives from the temporal character of climate risk. Research on EU security and external action shows that, despite growing acknowledgement of climate impacts, climate-related priorities have frequently been subordinated to more immediate policy concerns, with the overall rate of innovation slowing during periods when other agendas dominated (Youngs, 2014). New institutionalist work reaches a similar conclusion from a governance perspective: established routines and decision cycles embed long time horizons and reinforce path-dependent responses, limiting incentives for rapid change even when problems are well understood (Munck af Rosenschöld, Rozbicka and Lanér, 2014). These temporal dynamics weaken the traction of exceptional framing in the absence of acute disruption: when risks unfold gradually, claims of existential danger struggle to command the same political legitimacy as crises that materialise visibly and demand instant action. In short, the timing of climate impacts interacts with institutional rhythms in ways that make decisive responses less likely under "normal" politics (Youngs, 2014; Munck af Rosenschöld, Rozbicka and Lanér, 2014).

Acute crises and geopolitical conflicts often function as focusing events that reorder policy priorities and create favourable conditions for securitising moves. In the climate field, scholarship shows that environmental concerns gain greater strategic salience when they are linked to wider risks of instability and geopolitical contestation, rather than treated as stand-alone ecological problems (Trombetta, 2008; Dalby, 2013). Under such conditions, arguments that climate impacts or energy dependencies endanger core interests tend to resonate more strongly with audiences and institutions than in periods of routine politics. Work on European external action similarly notes that climate-related objectives have advanced most when external shocks have highlighted systemic vulnerabilities, whereas progress has been slower when competing agendas dominate (Youngs, 2014). These dynamics suggest a general mechanism: crises compress decision-time, concentrate authority, and lower procedural hurdles, thereby enabling exceptional measures that ordinary governance struggles to deliver. In short, shocks provide the temporal and political context in which securitisation claims are more likely to be authorised and translated into policy instruments, opening space for rapid reorientation of energy and climate strategies (Trombetta, 2008; Dalby, 2013; Youngs, 2014).

Russia's 2022 invasion of Ukraine transformed Europe's energy debate by foregrounding vulnerability to external fossil-fuel dependence and elevating energy policy onto a crisis footing. Analyses from the International Energy Agency link the ensuing energy crisis directly to the war and document a marked upward revision in renewable power forecasts, arguing that energy-security concerns and new policies catalysed faster deployment (IEA, 2022). Within the European Union, the Commission's REPowerEU initiative reframed the transition as a response to security risks; subsequent assessments note that the plan sought to accelerate the shift away from Russian fuels and raised the 2030 renewable energy target to 45%, alongside additional investment measures (Maliszewska-Nienartowicz, 2024; see also IEA, 2022). Early evidence on public attitudes suggests the war also increased support for clean-energy policies, at least in some contexts: a survey study in Switzerland reports broad backing across much of the political spectrum, while cautioning that translating sentiment into policy is not automatic (Steffen and Patt, 2022). In theoretical terms, the war functions as a focusing event that activated securitising moves and exceptional instruments. The expectation that states more exposed to Russian supplies faced stronger pressures to adopt accelerated measures follows directly from this logic.

3.1 Literature Review - From the "tragedy in the horizon" to security imperative

The relationship between energy and economic growth has long been recognised as central to modern development. Across successive waves of industrialisation, expansions in accessible energy have enabled productivity gains in industry, transport and households, while shortfalls have constrained output and raised costs (Stern, 2018). At the macro level, comparative studies report robust associations between energy use per capita and income, though the strength and direction of causality vary across time and place and remain contested in the empirical literature (Stern, 2018). This debate has sharpened as governments seek to reconcile growth with decarbonisation: efficiency gains and structural change can reduce energy intensity, yet achieving large absolute reductions in fossil use without harming performance has proved difficult at scale. Strategic analyses therefore characterise energy availability as a core condition for economic resilience and state capacity, highlighting why security of supply occupies a persistent place in policy agendas (Yergin, 2006). Framed this way, the politics of energy transition is not merely environmental; it is constitutive of growth models and competitiveness. This perspective sets up the review's next step: what happens to economies and policy when energy access is abruptly disrupted by shocks and crises.

Historical energy shocks illustrate how scarcity rapidly elevates energy policy to the top of political agendas and recalibrates governance instruments. The oil disruptions of the 1970s triggered by the Arab–Israeli war and embargo, and later by the Iranian upheaval, produced inflation, recession and acute supply insecurity across advanced economies. Governments responded with measures that have since become staples of energy security policy: diversification of suppliers and fuels, creation of strategic stocks, demand-management programmes, and institutional coordination at national and international levels (Yergin, 2006). These episodes also entrenched the idea that energy is a strategic vulnerability, not just a market commodity, shaping how leaders weigh risks and acceptable costs when supply is threatened. Subsequent scholarship connects this pattern to broader security logics: environmental and resource pressures gain traction when linked to geopolitical contestation and systemic stability, rather than treated as technocratic issues of efficiency alone (Dalby, 2013). The lesson for contemporary transition politics is twofold. First, shocks compress decision time and legitimise exceptional measures that normal procedures delay. Second, the direction of emergency responses is contingent: crisis can catalyse diversification and efficiency, but it can also reinforce fossil pathways if short-term security is prioritised over structural change (Yergin, 2006; Dalby, 2013).

Prior to the upheavals of 2022, the European Union positioned the European Green Deal as its flagship response to climate and energy challenges. Announced in December 2019, the initiative set out the goal of making Europe the first climate-neutral continent by 2050 and introduced a suite of measures including emissions reduction targets, carbon border adjustments, and mechanisms for a just transition (European Commission, 2019b). Crucially, the Green Deal was framed as a growth strategy rather than an emergency mobilisation. Its language emphasised opportunity, modernisation, and competitiveness, presenting decarbonisation as a pathway to sustainable prosperity rather than a response to existential threat (European Commission, 2019b; Wolf et al., 2021). This framing reflects a broader EU tradition of embedding climate objectives within long-term planning horizons and economic narratives, consistent with incremental policymaking under normal conditions (Youngs, 2014). Scholars note that this approach aimed to pre-empt political resistance by aligning climate policy with job creation and industrial renewal, thereby treating transition as a gradual reorientation rather than a rupture (Wolf et al., 2021). While ambitious in scope, the Green Deal illustrates the limits of incrementalism: it was designed to operate through negotiated reforms, financial incentives, and regulatory adjustments, rather than the suspension of ordinary politics. The contrast with later crisis-driven acceleration highlights the distinction between planned transition and securitised emergency action.

A recurrent finding in the transitions literature is that growth in renewable generation does not automatically translate into one-for-one displacement of fossil fuels. Instead, additions are often absorbed by rising overall demand and by the resilience of incumbent energy regimes, limiting substitution effects in the short to medium term. From a structural perspective, carbon lock-in ties infrastructures, market rules and investment cycles to fossil pathways, so that low-carbon options expand the system's capacity without necessarily displacing existing assets (Unruh, 2000). Complementing this, research on socio-technical regimes shows how incumbent actors exercise economic, institutional and discursive forms of power to defend market share, with the effect that "green" innovation can progress while the aggregate system remains anchored in coal, gas and nuclear production (Geels, 2014). These dynamics help explain why periods of rapid renewable deployment have not invariably produced proportional declines in fossil use: policy and market contexts shape whether new capacity substitutes or merely supplements. The implication for the EU's pre-2022 strategy is that scaling renewables, while necessary, was unlikely on its own to unwind entrenched fossil infrastructures; without measures that actively constrain incumbent assets and reconfigure system rules, additive growth risks leaving the core composition of the energy mix largely intact (Unruh, 2000; Geels, 2014).

The limited substitutive impact of renewables is closely tied to carbon lock-in — the mutually reinforcing web of infrastructures, technologies, regulations and market routines that stabilise fossil-fuel use over time (Unruh, 2000). Large, long-lived assets such as pipelines, refineries, gas-fired plants and storage facilities create sunk-cost pressures that bias future choices toward utilising existing capacity. Socio-technical scholarship adds that incumbent firms operate within regimes that align technical standards, supply chains, finance and skills with prevailing energy carriers, making it difficult for alternatives to displace entrenched systems even when they become cost-competitive (Geels, 2014). Incumbents also exert agency: they lobby to shape market rules, frame policy debates, and steer investment incentives in ways that protect legacy assets or open adjacent opportunities without undermining core business models (Kuzemko et al., 2016). On the demand side, efficiency improvements can generate rebound effects, where lower costs stimulate higher consumption, attenuating the net reduction in fossil use (Sorrell, 2009). Together, these supply- and demand-side mechanisms explain why scaling renewables under "normal" policy conditions may expand total system capacity without proportionately shrinking fossil output. Overcoming lock-in typically requires measures that alter expectations and asset valuations, tightening emissions constraints, reforming market design, withdrawing preferential treatments for fossil infrastructures, and aligning finance with phase-down trajectories, so that new low-carbon capacity replaces, rather than merely supplements, incumbent energy sources (Unruh, 2000; Geels, 2014; Kuzemko et al., 2016; Sorrell, 2009).

Whether renewable expansion substitutes for, or merely supplements, fossil energy depends heavily on national policy design and institutional capacity. Comparative work in energy policy and socio-technical transitions shows that supportive instruments (such as carbon pricing, the removal of fossil subsidies, stable support schemes for renewables, grid integration investments and streamlined permitting) condition the extent to which new low-carbon capacity displaces incumbent generation rather than adding to total supply (Sovacool, 2011; Bridge et al., 2013). Where policies prioritise security of supply through technology-neutral capacity mechanisms or maintain preferential treatments for fossil infrastructures, renewables tend to enter as additive sources, with substitution effects muted. By contrast, frameworks that combine ambitious emissions targets with consistent market signals and system planning are associated with higher observed displacement of fossil output. Recent comparative analyses also report substantial heterogeneity across OECD economies in the degree of substitution achieved, underscoring that technology cost declines alone do not guarantee structural change; outcomes hinge on the interaction of policy stringency, regulatory stability, and incumbent responses (Zheng and Kammen, 2021; York, 2012). In short, the literature indicates that policy architecture mediates the transition pathway: similar technologies can yield divergent system effects depending on how states align incentives, regulation and infrastructure to favour replacement over expansion (Sovacool, 2011; Bridge et al., 2013; Zheng and Kammen, 2021; York, 2012).

Temporal dynamics further complicate efforts to substitute away from fossil fuels. Decision cycles, budgeting processes and administrative routines embed long time horizons and incremental adjustment, which dampens incentives for rapid reorientation even when risks are well understood (Munck af Rosenschöld, Rozema and Frye-Levine, 2014). In the EU context, studies of external action and security policy likewise find that while climate risks have gained visibility, they have not consistently displaced more immediate agendas; rather, climate objectives tend to advance when linked to wider strategic concerns and stall when competing priorities dominate (Youngs, 2015). These patterns imply a timing problem: gradual, diffuse impacts struggle to command the urgency that would justify exceptional measures, especially in systems calibrated for negotiated, long-horizon change. As a result, routine governance is prone to defer or dilute measures that would accelerate structural substitution. This temporal inertia helps to explain why, prior to major shocks, the EU's transition strategy relied on long-term planning and incremental reforms, with substitution outcomes contingent on sustained policy alignment over time rather than on short bursts of action (Munck af Rosenschöld, Rozema and Frye-Levine, 2014; Youngs, 2015).

Building on the problem of temporal inertia, historical shocks show how crises compress decision-time and reorder priorities in ways that favour securitising moves. The oil disruptions of the 1970s made energy security a strategic concern across advanced economies, prompting measures that became standard repertoire: diversification of sources and fuels, creation of strategic stocks, demand-management programmes, and new coordination mechanisms at national and international levels (Yergin, 2006). Climate-related and resource pressures gain greatest political traction when linked to wider risks of instability and geopolitical contestation, rather than treated as stand-alone ecological problems (Dalby, 2013). Work on climate discourse similarly shows how framing environmental change as amplifying other vulnerabilities — conflict, displacement, food and water stress — helps move it onto high-level agendas (Trombetta, 2008). The common mechanism is that acute disruption clarifies exposure, concentrates authority, and lowers procedural hurdles, enabling instruments that routine governance struggles to deliver. At the same time, the direction of crisis responses is contingent: emergency measures can accelerate diversification, efficiency and low-carbon deployment, but they can also reinforce fossil pathways if short-term supply security is prioritised over structural change (Yergin, 2006; Dalby, 2013). These patterns prepare the ground for analysing how the post-2022 European response leveraged security framings to reconfigure energy policy.

Russia's 2022 invasion of Ukraine reoriented Europe's energy debate by exposing strategic dependence on external fossil supplies and pushing energy policy onto a crisis footing. Contemporary market assessments link the ensuing energy crisis directly to the war and document how security concerns, alongside new and revised policies, reshaped renewable prospects (IEA, 2022). In the European context, policy ambition visibly tightened: analyses in the IEA's *Renewables 2022* report note that the European Union moved to increase the renewable share in final energy consumption to 45% by 2030, up from the 40% previously under negotiation, and that the crisis sharpened attention to system bottlenecks such as permitting and grids (IEA, 2022). This marks a shift from the European Green Deal's pre-war incrementalism toward a securitised framing in which diversification, demand reduction and accelerated clean-energy deployment are treated as instruments of resilience rather than only as climate measures. At the discursive level, scholarship on climate and security has long argued that environmental pressures gain political traction when linked to wider risks of instability and geopolitical contestation; the post-2022 policy turn is consistent with that logic (Trombetta, 2008; Dalby, 2013). In short, the war acted as a focusing event that translated vulnerabilities into exceptional policy aims, with raised targets and an emphasis on overcoming implementation frictions indicative of a new, security-centred tempo for Europe's energy transition (IEA, 2022; European Commission, 2019b).

Post-2022, Europe's transition acquired a security-centred tempo consistent with securitisation dynamics. The Commission's REPowerEU re-specified renewables, efficiency and demand reduction as instruments of strategic autonomy and proposed a higher 2030 renewables target (45%), alongside permitting and grid reforms, marking a shifting from long-horizon planning to crisis governance *(European Commission, 2022b)*. The IEA, accordingly, revised up medium-term EU deployment, linking momentum to energy-security concerns and emergency policy support across power, heat and efficiency *(IEA, 2022)*. Scholarly assessments emphasise both the speed and the distributional trade-offs of this turn: Kuzemko et al. (2022) show how emergency measures reorder priorities with implications for sustainability and equity; Vezzoni (2023) notes tensions within REPowerEU between short-run supply security and structural decarbonisation trajectories. Sectoral expertise helps explain why a security frame resonated: Sharples (2020) and related OIES analyses highlight the system exposure created by Russia-related gas dependencies and the limited near-term substitutes within pipeline-constrained markets. Recent modelling adds that, relative to counterfactual baselines, Europe's war-scenario policy mix produces a faster transition pathway, consistent with a security-induced acceleration *(Yang et al., 2025)*. Read together, these sources indicate that crisis framing authorised exceptional instruments that routine EU governance had struggled to deliver, with measurable effects on targets and implementation.

Audience acceptance helps account for how securitising moves translated into policy. Eurobarometer surveys *before* the invasion already recorded strong public support for expanding renewables and reducing fossil-fuel imports from outside the EU, roughly 70% *(European Commission, 2019a; 2021)*. *After* the invasion, reported higher support (roughly 85%), with new Russia-specific items indicating broad approval for reducing dependency on Russian energy specifically, alongside continued backing for efficiency and clean-energy investment *(European Commission, 2022a; 2023; 2025)*. Micro-evidence complements this picture: Steffen and Patt (2022), in a post-invasion survey study, find robust cross-party support for clean-energy measures, while noting that converting sentiment into policy depends on design and distributional impacts. In securitisation terms, the alignment between elite framing (security and resilience) and audience preferences (renewables, lower import dependence) creates legitimacy for exceptional instruments (accelerated permitting, demand-reduction mandates, and state-backed investment) that incremental politics had deferred. The increase of support across pre- and post-war waves suggests continuity, while the *Russia-specific* emphasis post-2022 indicates how crisis sharpened the object of dependence. This conjunction of policy acceleration and public consent underpins the review's core inference: securitisation enabled a faster, if uneven, transition trajectory.

4.1 Methodology, Data, and Limitations

This chapter explains how I test whether the invasion of Ukraine accelerated renewable generation in EU member states with higher pre-war dependence on Russian gas. I outline a three modern DiD designs that speak to timing and intensity of exposure, drawing on recent work on continuous-treatment event-studies and staggered adoption with heterogeneous effects. I summarise how the data are constructed from harmonised European energy statistics and how inference and reporting follow current guidance on clustering and transparent DiD practice. I then describe the robustness and placebo checks and close with limitations that frame interpretation. The approach follows established advances in the literature on continuous-treatment DiD and event-studies, staggered designs, and applied inference standards (Callaway, Goodman-Bacon and Sant'Anna, 2024; Callaway, Goodman-Bacon and Sant'Anna, 2025; Sun and Abraham, 2021; Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020; Roth et al., 2023; Abadie et al., 2023; Cameron and Miller, 2015; Eurostat, 2022).

4.2 Research Design

This study tests whether the invasion of Ukraine acted as a securitising shock that accelerated renewable generation in EU member states with higher pre-war dependence on Russian gas, using modern difference-in-differences designs to map intensity and timing into causal estimates (see Table 1). It estimates effects on two outcomes, the share of renewable generation in gross electricity generation and renewable generation in gigawatt hours, as a function of pre-war exposure to Russian gas. Fundamentally, difference-in-differences compares changes in outcomes across units exposed to different treatment conditions under a parallel trends assumption. I employ three complementary variants. First, a continuous-treatment DiD recovers marginal effects per unit of exposure by interacting a dose measure of pre-war dependence with time; it is used when treatment varies in intensity rather than as a binary indicator, and relies on a generalized parallel trends condition across exposure levels, conditional on fixed effects and covariates (Callaway, Goodman-Bacon and Sant'Anna, 2025; Roth et al., 2023). Second, a continuous-treatment event study interacts relative time with the same dose to diagnose pre-trends and trace post-shock dynamics, which clarifies the timing of effects and supports transparent aggregation for reporting (Callaway, Goodman-Bacon and Sant'Anna, 2024; Sun and Abraham, 2021). I also report a categorical DiD that bins exposure into low, medium, and high groups to probe non-linearities while preserving interpretability under the same identifying assumption (Roth et al., 2023). Third, a Callaway and Sant'Anna group-time ATT estimator is used for staggered adoption, reporting cohort-time effects with event-time and overall aggregations; it is appropriate when treatment timing varies and requires cohort-specific parallel trends, no anticipation, and absorbing treatment once adopted

Table 1. Overview of difference-in-differences designs

Design	Treatment Timing	Exposure	Control group	Estimand
Callaway & Sant'Anna (C&S)	Staggered adoption (3 month drop to ≤10% RU share, post-2022)	Binary (treated once cutoff reached)	Never-treated / Not-yet-treated	ATT(g,t)
Continuous DiD (pre/post)	Common shock (March 2022)	Continuous (% pre-war RU dependence)	Lower-dependence countries	Average post-period ATT
Continuous DiD (event-time)	Common shock, relative months from invasion	Continuous (% pre-war RU dependence)	Lower-dependence countries	Dynamic ATT(g,t+k)
Categorical DiD	Common shock (March 2022)	Low (<10%) Medium High dependence bins	Other bins	Group ATT
Placebo C&S (Green Deal)	Forced treatment Jan 2020	Binary based on C&S design	Never-treated / Not-yet-treated	ATT(g,t) (placebo)

(Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020).

For the continuous (OLS) specification, I interact a post-invasion indicator with pre-war Russian-gas dependence, defined as the 2019–2021 average and rescaled to percentage points so coefficients read per one percentage point, with effects also reported per ten points for interpretation; estimation includes country and calendar-month fixed effects with standard errors clustered by country, which follows guidance on absorbing time-invariant heterogeneity and common shocks while reporting clustered inference (Cameron and Miller, 2015; Abadie et al., 2023). In adjusted variants I include log GDP per capita (PPS), log energy use per capita, the fossil share of the energy mix, gas storage, and population. To probe timing, I estimate a continuous-treatment event study by replacing the post indicator with relative-time dummies around March 2022 and interacting each with exposure, which provides a transparent check of pre-trends and a dynamic profile of post-shock responses consistent with recent advice for event-time reporting under heterogeneous effects (Sun and Abraham, 2021; Callaway, Goodman-Bacon and Sant'Anna, 2024). Dynamic specifications report coefficients at leads ($k<0$) and lags ($k>0$) relative to March 2022 by interacting relative time with exposure. These are event-time lags and not lagged dependent variables. These dynamic models use the same fixed effects and. I complement this with a categorical design that bins exposure into low, medium, and high to assess non-linearities and aid interpretability (Roth et al., 2023). The categorical event-time models are estimated with country fixed effects only to preserve variation in the relative-time indicators and do not add time-varying controls.

Because countries reduce dependence at different dates, I estimate a cohort-based staggered design using the Callaway and Sant'Anna group-time ATT on a country–quarter panel from 2020Q1 to 2024Q4. Treatment is the first quarter after March 2022 that contains three consecutive months at or below ten percent Russian share, and treatment is absorbing. The primary comparison is not-yet-treated, with never-treated as robustness, and inference uses the multiplier bootstrap clustered by country. To stabilise small cohorts, first-treatment quarters are pooled into waves (Table 2). I report cohort-time effects and aggregate them into an event-time profile and an overall average. The adjusted staggered specification includes log GDP per capita as a baseline covariate. Identification requires cohort-specific parallel trends and no anticipation, which I probe using pre-treatment dynamics and a timing placebo set in 2020Q1, alongside on–off covariate checks and alternative outcomes (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020; Callaway, Goodman-Bacon and Sant'Anna, 2024; Christensen and Miguel, 2018; Eurostat, 2022).

Table 2. C&S Case coverage and treatment timing

Treatment wave	First treatment quarter	Number of countries	Avg pre-war RU gas dependence (%)	Quarters pre-treatment	Quarters post-treatment
Wave 1 (Q18)	2022Q2	1	53.60	10	11
Wave 2 (Q20)	2022Q3–Q4	2	24.25	12	9
Wave 3 (Q21)	2023Q1–Q2	2	80.64	13	8
Never-treated		22	<10%		

Note: Treatment waves defined by Callaway & Sant'Anna grouping rule (≤10% Russian gas share for 3 consecutive months, post-2022). Pre-war dependence calculated as average 2019–2021 share of Russian gas in total imports. Authors' coding from Eurostat gas import data.
Note 2: Q18/Q20/Q21 are quarters of year from beginning of data.

4.3 Scope, Data and Handling

The analysis covers the European Union with a target of EU-27, with Cyprus excluded due to missing series, which yields EU-26 in estimation. I assemble a country–month panel for 2018 to 2024 that feeds both the monthly designs and a country–quarter panel for 2020Q1 to 2024Q4 used in the staggered design. Outcomes are measured from harmonised European energy statistics (Eurostat): the share of renewable generation in gross electricity generation and renewable generation in gigawatt hours. Exposure is pre-war dependence on Russian gas, defined as the average share of Russian imports in total gas imports during 2019–2021 and used as a continuous dose. Structural covariates are merged by calendar year into the monthly frame and include log GDP per capita in purchasing power standards, log energy use per capita, the fossil share of the energy mix, gas storage, and population. For the quarterly panel, I average shares and sum levels within quarters, retaining the same variable definitions. The post-invasion window is defined relative to March 2022 to align timing across designs. All series

Table 3. Main data, definitions and sources

Variable	Definition	Source - Eurostat codes	Frequency	Coverage (EU-27)
Renewable share (%)	Share of renewable electricity in gross generation	(nrg_cb_pem)	Monthly → Quarterly	2018–2024
Renewable output (gwh)	Total renewable electricity generation, log-transformed	(nrg_cb_pem)	Monthly → Quarterly	2018–2024
Russian gas dependence (%)	Share of Russian gas in total gas imports (made by writer)	(nrg_ti_gasm) Derived: Russia/Total x100	Monthly (pre-2022)	Mean Jan 2018 – Feb 2022
Gdp per capita (log, PPS)	GDP per capita in purchasing power standards, log-transformed	(nama_10_pc)	Annual → Monhly → Quarterly	2018–2024
Population	Resident population at mid-year	(demo_pjan)	Annual → Monthly	2018–2024
Total energy supply (Gwh)	Total energy Supply	(nrg_bal_c)	Annual → Monthly	2018–2024
Energy per capita (log, Gwh)	Total energy consumption per capita, log-transformed	Derived: (nrg_bal_c)/Population x1000 (Mwh – Gwh)	Annual → Monthly	2018–2024
Fossil share of energy mix (%)	Share of fossil fuels in total energy balance (agg of multiple variables)*	Derived: (nrg_bal_c)	Annual → Monthly	2018–2024
Gas storage (mcm)	Volume of gas in storage at month-end	Eurostat	Monthly → Quarterly	2018–2024

*: See annex for further information.
Note: monthly data originally covered to 2025, however, none of it was included in the research due to missing data for many countries.

and transformations follow the Eurostat harmonised framework for electricity and natural gas statistics, with attention to revisions, comparability across member states, and documentation of data quality and coverage (Eurostat, 2022).

The denominator excludes intra-EU re-exports so the dose measures external dependence rather than internal trade flows. Post-2022 origin attribution can be noisy where LNG cargos are routed via intermediaries; the operative measure remains partner-identified imports, and results are reported for a fixed data vintage to avoid rolling revisions (Eurostat, 2022). The monthly panel is unbalanced where series have gaps. I document missingness, exclude Cyprus for persistent gaps, and otherwise retain observed months without imputation. Units and transforms follow a simple rule: renewable generation share is in percentage points, renewable generation in gigawatt hours is in levels, and log transforms are reserved for robustness. Quarterly aggregation averages shares and sums levels using calendar quarters. Structural controls are merged by calendar year: GDP per capita in purchasing power standards (log), energy use per capita (log), fossil share of the energy mix, gas storage stock, and population, each taken from harmonised European energy and national accounts statistics with consistent codes from Eurostat. No winsorisation or outlier trimming is applied. A data dictionary (Annex 1) and construction log list source tables, units, and transformations so the panel can be rebuilt and cross-checked for coverage and revisions (Eurostat, 2022).

4.4 Limitations

Identification rests on parallel trends tailored to each design. For the continuous specifications the assumption is a generalized parallel trend across exposure levels, which cannot be tested directly and may be sensitive to how effects aggregate over time and dose (Callaway, Goodman-Bacon and Sant’Anna, 2025; Roth et al., 2023). In event-time settings, heterogeneous timing and effects can bias conventional two-way fixed effects, which motivates the use of designs that construct uncontaminated dynamic paths, yet aggregated parameters can still reflect composition and weighting choices (Sun and Abraham, 2021; Callaway, Goodman-Bacon and Sant'Anna, 2024). Staggered estimates require cohort-specific parallel trends, no anticipation, and absorbing treatment; small early cohorts can yield imprecise group-time effects and raise nontrivial aggregation decisions (Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020). Inference clusters by country, but a modest number of clusters and serial correlation can affect size; the multiplier bootstrap helps in the staggered design, though it is not a cure-all (Abadie et al., 2023; Cameron and Miller, 2015). Data constraints matter. Partner-identified import shares may misclassify Russian content after 2022, official energy statistics are subject to revisions, and the panel is unbalanced with Cyprus excluded despite harmonisation (Eurostat, 2022). Seasonality is absorbed by time fixed effects, but weather and technology shocks are not modelled directly. The post-2022 window is short relative to investment cycles, so estimates capture short-run acceleration in renewable generation rather than long-run structural change.

Results are presented in a compact bundle that follows current guidance for transparent DiD reporting. For continuous specifications I report the average post effect per one percentage point of exposure and rescale to per ten points for interpretation, alongside a dynamic profile that plots coefficients at leads and lags relative to March 2022 with confidence intervals and joint tests of pre-trends. For the categorical specification I show event-time paths for low, medium, and high exposure to visualise possible non-linearities. For the staggered design I display cohort-time effects and their aggregation into an event-time profile and an overall average, using not-yet-treated as the primary comparison and never-treated as robustness. Tables state fixed effects, clustering level, sample windows, and the covariates included, and figures use consistent units for renewable generation outcomes to avoid scale confusion.

Sensitivity is summarised through changes in covariate sets, alternative outcome definitions, and the timing placebo. This presentation is consistent with recent recommendations on event-study practice under heterogeneous timing, on decomposition and aggregation in staggered designs, and on clear communication of identification and inference choices in applied work (Sun and Abraham, 2021; Goodman-Bacon, 2021; Callaway, Goodman-Bacon and Sant'Anna, 2024; Roth et al., 2023; Cameron and Miller, 2015).

A final limitation concerns the measurement of securitisation. In the security studies literature securitisation is a discursive and intersubjective process in which actors frame an issue as a security threat and audiences accept that framing, often enabling exceptional measures (Buzan, Wæver and de Wilde, 1998; Balzacq, Léonard and Ruzicka, 2015). A quantitative panel cannot test that speech act directly. The objective here is narrower and empirical. I test whether actions plausibly linked to a securitising turn after the invasion are associated with accelerated renewable generation where pre-war dependence was higher. The designs estimate the consequences of that turn rather than the discursive act itself. To reduce the gap between mechanism and measure, the analysis later triangulates with public opinion indicators and policy shifts that align with a security framing of renewables, while remaining clear that these are consistency checks rather than proof of securitisation (Kuzemko et al., 2020; Vezzoni, 2023). With these caveats in view, the analysis proceeds by first describing cross-country patterns and timing, then presenting the main estimates and dynamic profiles, followed by robustness checks and mechanism evidence that together speak to the size, timing, and credibility of the estimated effects on renewable generation.

5.1 Analysis and Results – Difference-in Difference Evidence on Post-Invasion Renewable Uptake?

This study now turns to interpreting the empirical results, proceeding from descriptive evidence to main estimates, then to robustness and mechanisms, and ending with a falsification contrast. The results are reported in stages to make the logic transparent: first, descriptive visuals establish the dispersion in pre-war Russian gas dependence and the baseline paths of renewable generation across member states; second, the core estimates are presented using multiple designs that were already specified in the methodology, allowing the same question to be examined under different functional forms and identifying assumptions; third, robustness checks and a placebo anchored on the pre-war Green Deal timeline assess whether the patterns can plausibly be attributed to the post-invasion security shock rather than generic policy drift or climate concern. Throughout, emphasis is on triangulation across designs, with the categorical and Callaway–Sant'Anna estimators providing a disciplined complement to the continuous-treatment approach (Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Callaway, Goodman-Bacon and Sant'Anna, 2025). Substantively, the interpretation is tethered to the European Commission's characterisation of a "double urgency to transform Europe's energy system" and the commitment to "end [the EU's] dependence on Russian fossil fuels," which frames the post-2022 period as a security-driven acceleration rather than a routine continuation (European Commission, 2022). The final part of this section deliberately withholds the placebo comparison until after the full set of estimates, so that the Green Deal exercise functions as a decisive credibility check rather than a preliminary result.

Figure 1. Average Russian Gas Dependence, 2019–2021 (pp) — by Country

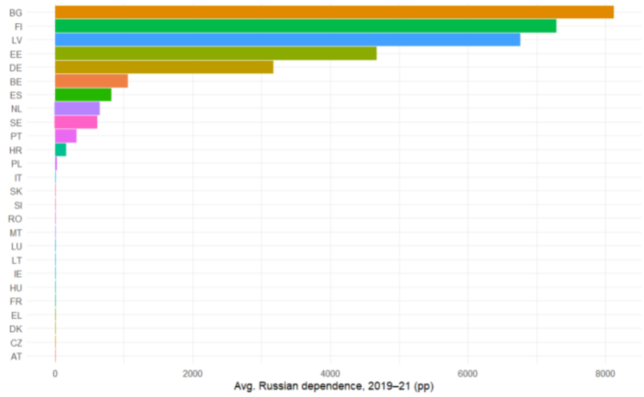


Figure 2a – 2b Renewables Share and Levels Over Time
High (>40 pp) vs Low (≤10 pp) Pre-war Dependence

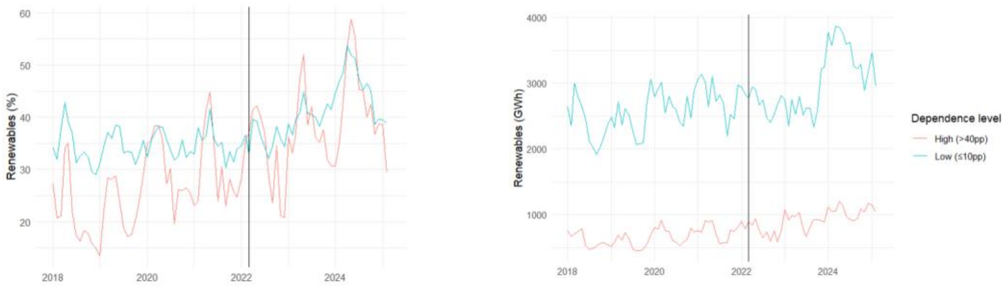


Figure 1 ranks average pre-war Russian gas dependence from highest to lowest and the pattern is top-heavy: Bulgaria close to 95 percentage points, Finland around the mid-80s, Latvia in the low-80s, Estonia near the mid-50s, with a mid-tier around 20–35 points that includes Germany and Belgium, and many members in single digits and zeroes. This gradient is reflected in the summary statistics. Figure 2 carries the heterogeneity into outcomes: before 2022, low and high exposure groups move without persistent divergence, while after the invasion the high-exposure group lifts more sharply in shares, even as the low-exposure group retains a higher level of generation in GWh due to the imbalance of what is considered "high exposure", as Figure 1 shows only 4 countries are considered as having a high pre-dependence. Read against the energy-security literature on "structural dependence" and lock-in through pipeline topology and long contracts, which simultaneously heighten vulnerability and sharpen substitution incentives once shocks bind, the descriptive evidence suggests room for a security-driven acceleration in renewables rather than routine continuation (Sharples 2020; Kuzemko et al. 2022). Framed by the Commission's call for a "double urgency to transform Europe's energy system" and to "end the EU's dependence on Russian fossil fuels," these facts motivate the causal tests that follow and provide a baseline for interpreting magnitudes (European Commission 2022; IEA 2022; Steffen and Patt 2022).

Table 4a. Descriptives (Overall)

Variable	Mean	SD	Min	Max	N
Renewables share (%)	34.60	22.76	0.00	93.71	2236
Renewables (GWh)	2352.51	3189.87	0.00	20333.58	2236
Pre-war dependence share (pp)	14.85	28.12	0.00	93.27	2262
Log GDP per capita (PPS)	10.41	0.35	9.70	11.47	2184
Log energy consumption per capita (MWh)	3.60	0.33	2.90	4.48	1872
Gas storage level (mcm)	3084.47	4841.12	0.00	24152.00	2108

Table 4a. Descriptives (Pre)

Variable	Mean	SD	Min	Max	N
Renewables share (%)	31.47	21.72	0.00	87.88	1300
Renewables (GWh)	2141.42	2921.45	0.00	13288.74	1300
Pre-war dependence share (pp)	14.85	28.12	0.00	93.27	1300
Log GDP per capita (PPS)	10.32	0.35	9.70	11.40	1300
Log energy consumption per capita (MWh)	3.62	0.34	2.90	4.48	1300

Table 4c. Descriptives (Post)

Variable	Mean	SD	Min	Max	N
Renewables share (%)	38.96	23.46	0.00	93.71	936
Renewables (GWh)	2645.69	3509.58	0.00	20333.58	936
Pre-war dependence share (pp)	14.85	28.12	0.00	93.27	962
Log GDP per capita (PPS)	10.53	0.32	10.02	11.47	884
Log energy consumption per capita (MWh)	3.56	0.30	2.98	4.26	572
Gas storage level (mcm)	3299.93	4979.37	0.00	24145.00	874

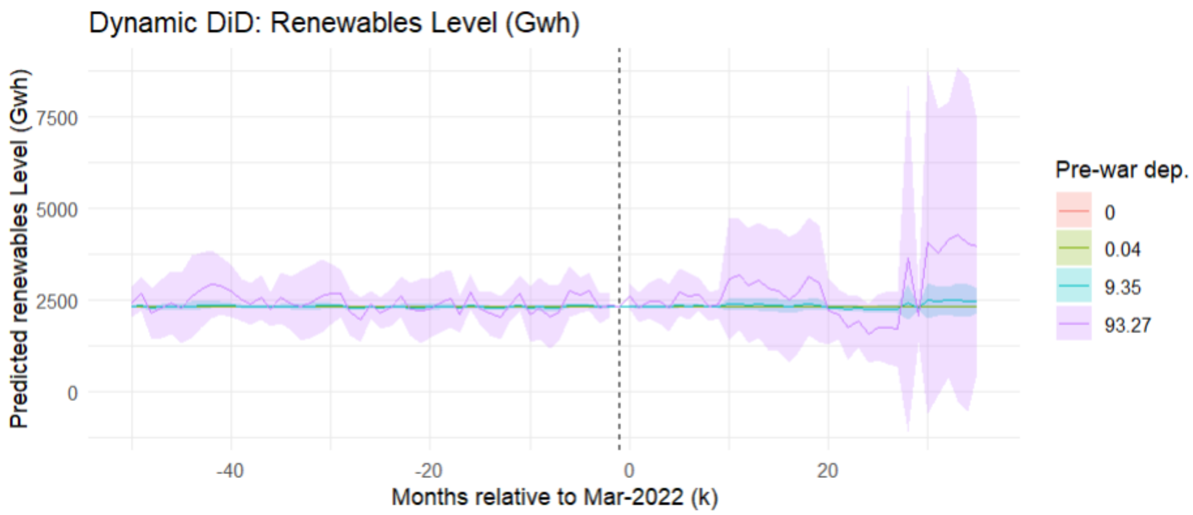
Tables 4a (Overall), 4a (Pre) and 4c (Post) document a steep exposure gradient and meaningful post-2022 movement in outcomes. Pre-war dependence averages 14.85 pp with a wide SD of 28.12 and a maximum of 93.27, confirming that a few cases sit at very high exposure while many lie in single digits; this variable is fixed by construction from 2019–2021 and carried to all observations. Renewable generation increases from 31.47 percent pre to 38.96 percent post, a 7.49 pp rise, which is about 24 percent relative to the pre mean (7.49/31.47). In levels, generation rises from 2,141.42 GWh to 2,645.69 GWh (+504.27 GWh, roughly 24 percent of the pre mean). Dispersion remains large and slightly widens in shares (SD 21.72 to 23.46; max 87.88 to 93.71), consistent with heterogeneity in capacity additions. Gas storage increases from 2,931.87 mcm to 3,299.93 mcm, while log GDP per capita edges up from 10.32 to 10.53 and log energy use per capita dips from 3.62 to 3.56, suggesting modest macro recovery with some demand restraint. The post window has fewer observations (936 vs. 1,300 for the main outcomes), reflecting shorter exposure rather than lost coverage. Read with Figure 1's rank ordering and Figure 2's pre-2022 paths that do not exhibit persistent divergence, these facts supply the empirical backdrop for the difference-in-differences tests and align with the energy-security account that structural dependence creates vulnerability but also "sharpens substitution incentives when a shock arrives," a dynamic reinforced by the Commission's call for a "double urgency to transform Europe's energy system."

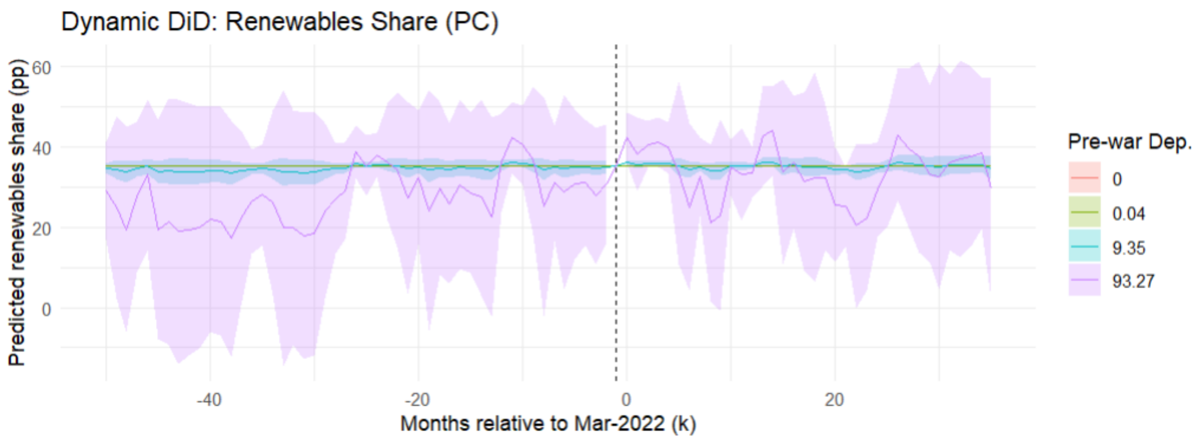
Table 5. TWFE (Pre-war dependence × Post) — PC & GWh

Outcome	Specification	Estimate	SE	CI low	CI high	p-value
Renewables share (%)	TWFE (no controls)	0.066	0.045	-0.023	0.154	0.160
Renewables share (%)	TWFE (controls)	0.077	0.052	-0.026	0.179	0.155
Renewables (GWh)	TWFE (no controls)	3.49	5.24	-6.78	13.80	0.512
Renewables (GWh)	TWFE (controls)	1.50	3.56	-5.48	8.48	0.677

Table 5 shows that the post × exposure coefficient on renewable generation share is 0.066 without controls (SE 0.045, 95% CI −0.023 to 0.154, p = 0.160) and 0.077 with controls (SE 0.052, 95% CI −0.026 to 0.179, p = 0.155). Interpreted per 10 percentage points of pre-war dependence, these imply gains of about 0.66–0.77 percentage points, with 95% intervals of roughly −0.23 to 1.54 and −0.26 to 1.79. Relative to the pre-period mean of 31.47 percent, the point estimates correspond to an 8–10 percent increase. In levels the association is weaker and imprecise: 3.49 GWh per point without controls (SE 5.24, p = 0.512; about −67.8 to 138 GWh per 10 points) and 1.50 GWh with controls (SE 3.56, p = 0.677; about −54.8 to 84.8 GWh per 10 points). These results do not reject the null at conventional thresholds, but they are directionally consistent with the descriptive acceleration among highly exposed states and are presented in line with guidance on staggered timing, composition, and inference in DiD applications (Bertrand, Duflo and Mullainathan, 2004; Goodman-Bacon, 2021; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; Callaway, Goodman-Bacon and Sant'Anna, 2025).

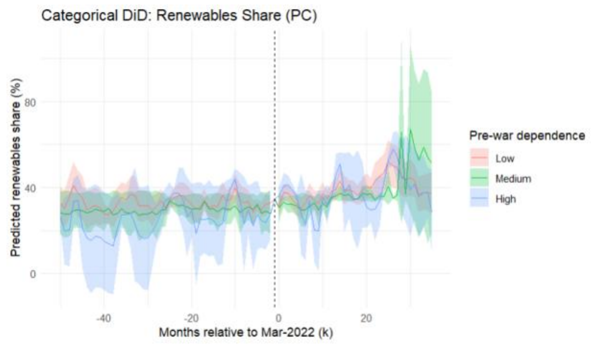
Figure 3a – 3b. Continuous Dynamic DiD (event-time)

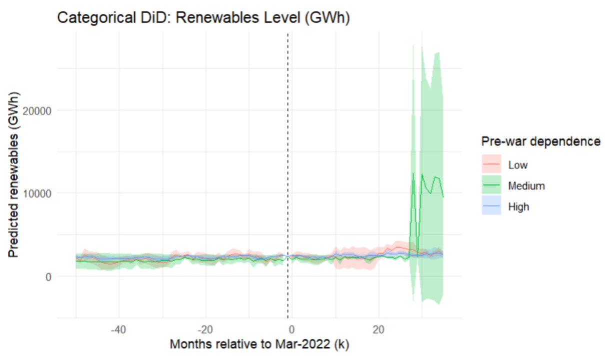




The continuous event-time plots (Figure 3a, 3b) show flat and statistically indistinguishable pre-invasion profiles across exposure bins, which is consistent with the identifying requirement that "pre-treatment outcomes do not trend differently by treatment timing" (Sun and Abraham, 2021; Callaway and Sant'Anna, 2021). Around the invasion quarter the highest-exposure line exhibits a discrete upward break in renewable generation that persists through the subsequent quarters, while the lowest-exposure line remains comparatively stable. In shares, the divergence is visible within the first few months and remains positive thereafter; in levels, the same pattern appears but with wider confidence bands, indicating greater uncertainty about the exact magnitude. This shape aligns with the descriptive contrasts and with the policy environment that the Commission framed as a "double urgency to transform Europe's energy system" and to "end the EU's dependence on Russian fossil fuels," which plausibly concentrated deployment pressure where reliance had been greatest (European Commission, 2022; IEA, 2022; Kuzemko et al., 2022; Sharples, 2020). The figure therefore complements the baseline estimates by showing that the association strengthens precisely when the security shock binds, without systematic lead effects that would undermine a difference-in-differences reading.

Figure 4a - 4b. Categorical exposure design (Low / Medium / High)





The categorical event-time profiles reinforce the dose–response pattern using a simpler grouping of countries by pre-war dependence. Before 2022 the predicted paths for low, medium and high exposure track each other without systematic divergence in either shares or levels. After the invasion marker the high-dependence group pulls away: in shares the trajectory lifts above the low- and medium-exposure lines and remains higher through the observed window, while in levels the same ordering appears with wider intervals, especially in the right tail where the high group exhibits a marked post-2023 rise. This pattern is consistent with the descriptive contrast in Figure 2, the cross-sectional gradient in Figure 1, and the baseline coefficients in Table 5 that point to larger post-2022 increases where exposure was greater. Substantively, it accords with accounts of structural dependence and securitisation that describe how infrastructure lock-in and long contracts make highly reliant states both more vulnerable and more likely to prioritise deployment once the shock binds and policy frames a "double urgency to transform Europe's energy system" and to "end the EU's dependence on Russian fossil fuels" (Sharples, 2020; Kuzemko et al., 2022; European Commission, 2022; IEA, 2022).

Table 6. Treatment Waves & Cohort Descriptives

Wave	Countries (N)	Mean Pre. dep. (pp)	Median pre-dep (pp)	IQR pre-dep (pp)	Countries list
Control	21	5.8389	0.0000	1.73750	Austria, Bulgaria Croatia, Czechia France, Greece Hungary, Ireland, Italy, Lithuania Luxembourg, Malta Netherlands, Poland Portugal, Romania Slovakia, Slovenia Spain, Sweden
2022Q2	1	53.6003	53.6003	0.00000	Estonia
2022H2	2	24.2527	24.2527	12.12444	Belgium Germany
2023H1	2	80.6447	80.6447	2.96629	Finland Latvia

The Callaway–Sant'Anna estimates indicate a positive but imprecise average post-treatment effect on renewable generation when cohorts are aggregated. In Table 7 the overall ATT on the renewable share is 3.35 percentage points using never-treated controls and 3.42 points using not-yet-treated controls (SE 2.84 in both cases, 95% CIs −2.22 to 8.92 and −2.15 to 8.98). For levels, the corresponding point estimates are 559.84 GWh and 559.68 GWh, with large standard errors around 720 GWh. The event-time plots, especially the renewable GWh generation, complement these averages: pre-treatment coefficients oscillate around zero without systematic drift, and post-treatment effects turn positive and grow over the horizon while confidence intervals widen, a shape consistent with heterogeneous timing handled by the C&S framework (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). Taken with the continuous-treatment results, this pattern suggests that countries entering treatment behave similarly before first exposure and then shift upward thereafter, in line with the policy environment described by the Commission as a "double urgency to transform Europe's energy system" and a commitment to end dependence on Russian fossil fuels, which plausibly focused deployment where vulnerability had been greatest (European Commission, 2022; Kuzemko et al., 2022; Sharples, 2020).

Table 7. C&S Overall ATT (Renewables: % and GWh)

Control group	Outcome	Est	SE	CI low	CI high
Never-treated	Renewables share (%)	3.35	2.84	-2.22	8.92
Not-yet-treated	Renewables share (%)	3.42	2.84	-2.15	8.98
Never-treated	Renewables (GWh)	559.84	720.20	-851.75	1971.43
Not-yet-treated	Renewables (GWh)	559.68	715.32	-842.35	1961.71

Figure 5a – 5d. C&S event-study (War), overall

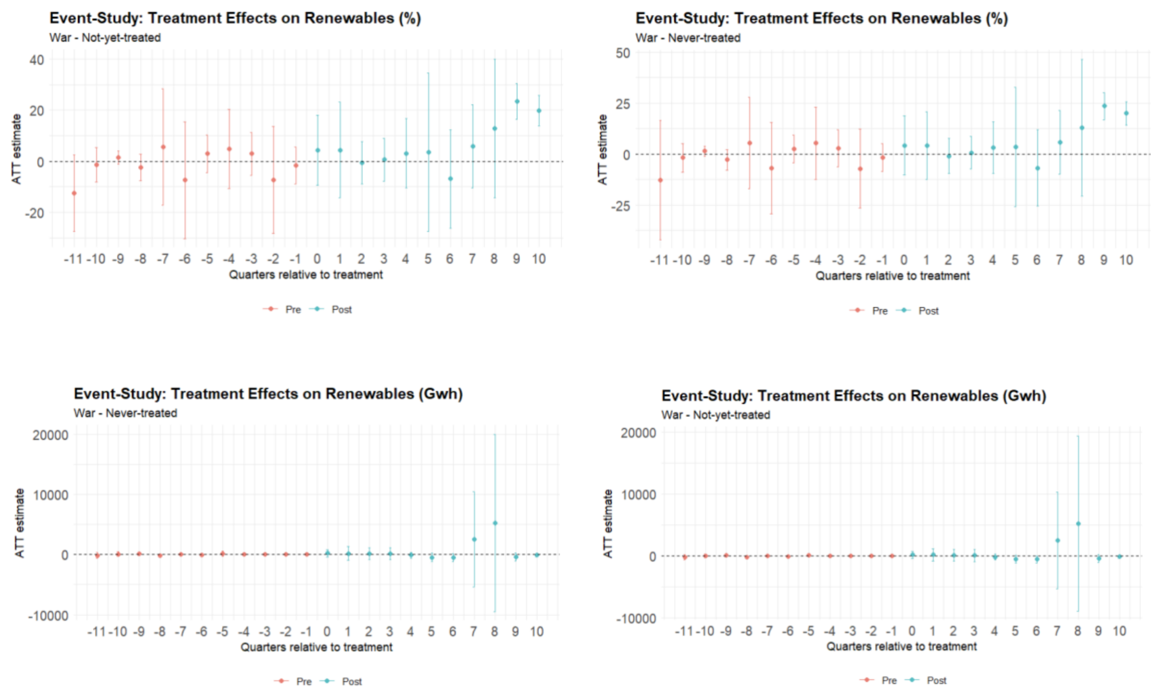


Table 8 shows pronounced cohort differences that align with the exposure gradient in Table 5. The first wave records an average treatment effect on the renewable share of 7.38 percentage points using either control group (SE 1.22–1.35), while the third wave is also positive at 6.50 points with wider uncertainty (SE 4.41–4.92). The second wave is small and slightly negative at −1.91 points (SE about 2.1). In levels, the only sizable point estimate is in the second wave at 1,476 GWh, though standard errors are very large, whereas wave one is −118.74 GWh and wave three is −4.46 GWh, both indistinguishable from zero given their intervals. These patterns are consistent with the cohort composition in Table 5: wave three comprises the highest-exposure states on average (mean pre-war dependence 80.64 percentage points, Finland and Latvia), wave one is also highly exposed (53.60, Estonia), and wave two sits in a medium range (24.25, Belgium and Germany). The wave-specific event-time plots echo this ranking, with pre-treatment coefficients oscillating around zero and post-treatment effects lifting most clearly for waves one and three as horizons lengthen. Substantively, this ordering fits the energy-security account in which structural dependence and abrupt supply risk intensified the incentive to prioritise renewable generation once the shock bound, an interpretation that sits comfortably with the Commission's call to "end the EU's dependence on Russian fossil fuels" and with analyses stressing how infrastructure lock-in both heightens vulnerability and creates a pivot once the security frame takes hold (European Commission, 2022; Sharples, 2020; Kuzemko et al., 2022; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021).

Table 8. C&S Wave-Specific ATT

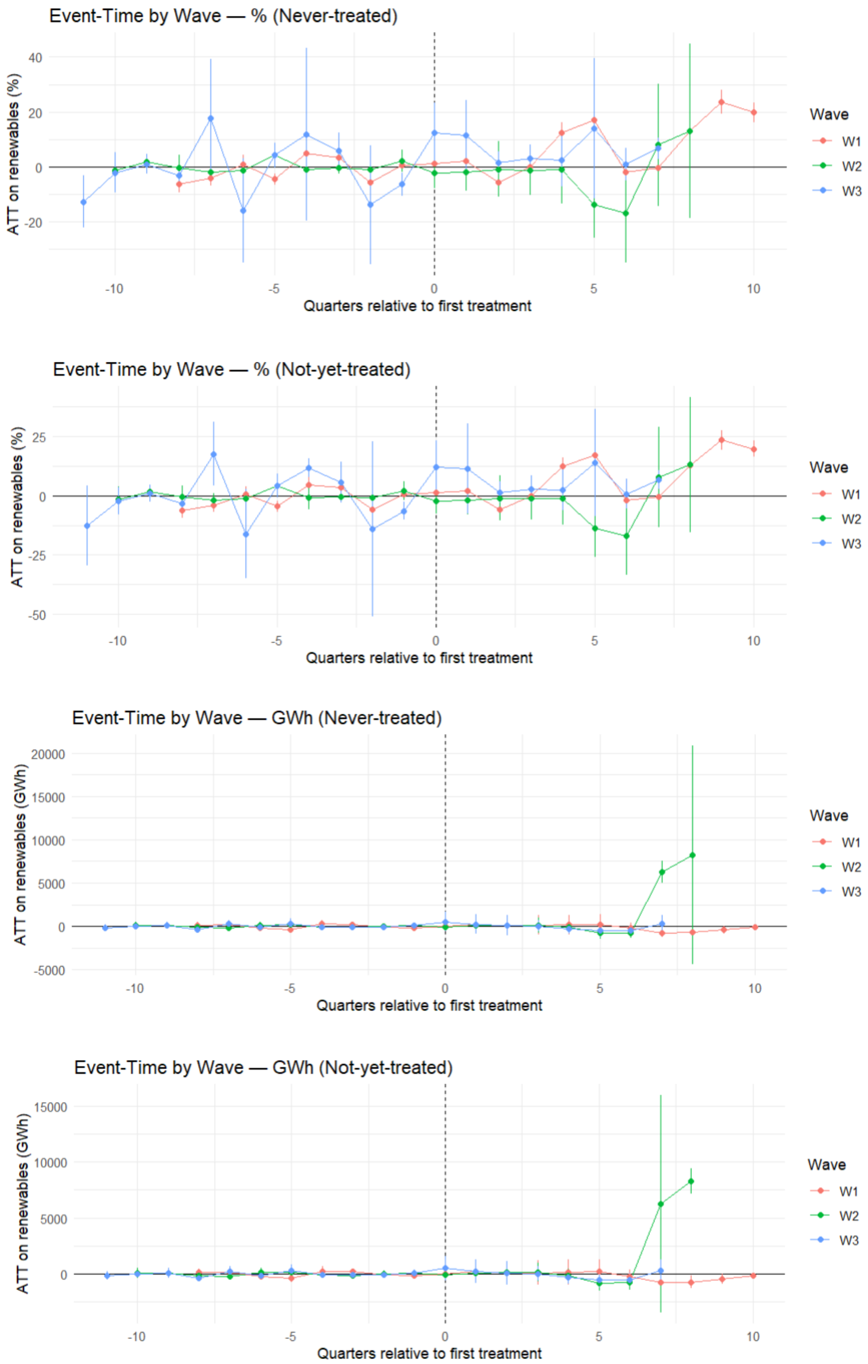
Renewables share (%)

Wave	Control grou	ATT	SE
W1	Never-treated	7.38	1.22
W1	Not-yet-treated	7.38	1.35
W2	Never-treated	-1.91	2.08
W2	Not-yet-treated	-1.91	2.17
W3	Never-treated	6.50	4.92
W3	Not-yet-treated	6.50	4.41

Renewables share (GWh)

Wave	Control group	ATT	SE
W1	Never-treated	-118.74	198.56
W1	Not-yet-treated	-118.74	181.55
W2	Never-treated	1476.13	1939.88
W2	Not-yet-treated	1476.13	297.42
W3	Never-treated	-4.46	262.27
W3	Not-yet-treated	-4.46	254.89

Figure 6a - 6d. C&S event-study (War), by wave

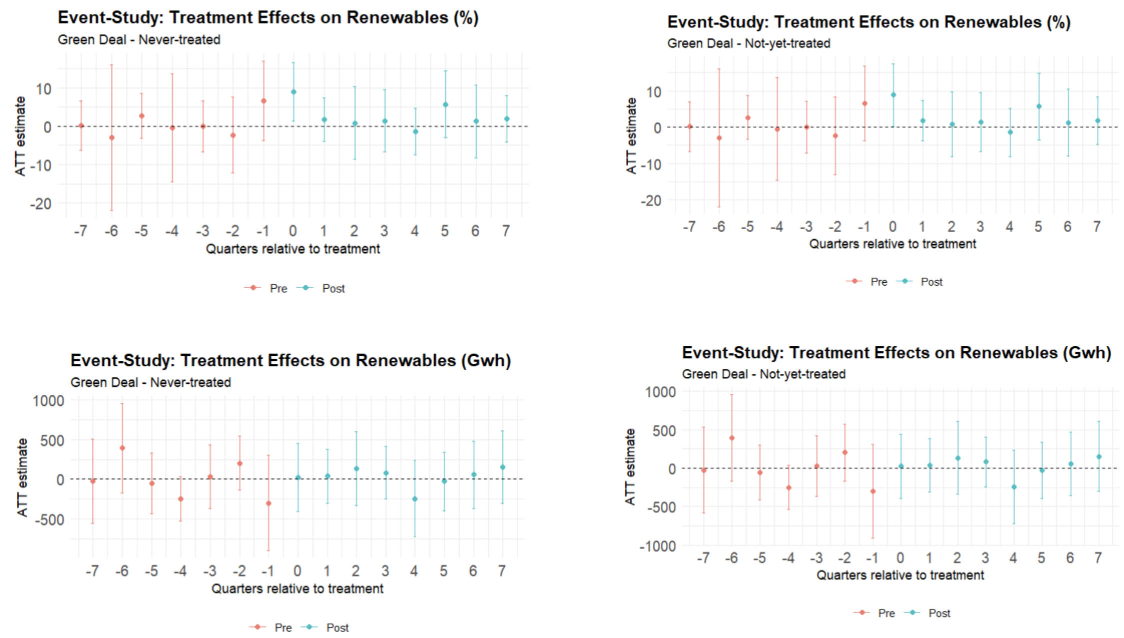


The robustness checks point in a consistent direction and the placebo exercise provides a decisive contrast. First, the staggered results are stable across control groups: the overall ATT in Table 7 is 3.35 percentage points using never-treated countries and 3.42 using not-yet-treated, with identical standard errors, which indicates that composition of the comparison group is not driving the sign of the estimates (Callaway and Sant'Anna, 2021). Second, using alternative outcomes leaves the qualitative pattern intact: the share estimates are positive though imprecise, while the level estimates are noisier but do not contradict the direction of change, a gap that is plausible given cross-sectional differences in system size. Third, the Green Deal placebo, which forces treatment in 2020Q1, shows no structural break: event-time coefficients fluctuate around zero both before and after the placebo date in percentage and GWh panels, and the confidence intervals routinely cover zero over the entire horizon. This is the contrast this paper sought to stage. The C&S war-timed profiles rise after first treatment, whereas the placebo profiles do not, which strengthens a security-shock interpretation over a generic policy-drift or climate concern story. Reporting follows recommendations on pre-trend visualization, appropriate comparison groups, and attention to serial correlation and composition in panel DiD (Bertrand, Duflo and Mullainathan, 2004; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Roth et al., 2023).

Table 8. Placebo (Green Deal) event-study

Control group	Outcome	Controls	Est	SE	CI low	CI high
Never-treated	Renewables share (%)	+ log GDP per capita	2.54	1.98	-1.35	6.43
Not-yet-treated	Renewables share (%)	+ log GDP per capita	2.54	2.00	-1.37	6.45
Never-treated	Renewables Levels (GWh)	+ log GDP per capita	27.10	114	-196	250
Not-yet-treated	Renewables Levels (GWh)	+ log GDP per capita	27.10	104	-177	231

Figure Xa - Xd. Placebo (Green Deal) event-study



Thus, the shape and timing of the estimates read plausibly through a securitisation mechanism. Descriptively, renewable generation rises by 7.49 percentage points from the pre-period mean of 31.47 to 38.96 after 2022, with the high-exposure group in Figure 2 accelerating more sharply than the low-exposure group. In the continuous design, the point estimates imply roughly 0.66–0.77 percentage-point higher gains per 10 percentage-points of pre-war dependence, while the staggered design finds cohort effects that are largest where exposure and timing bite most strongly, for example 7.38 percentage points in Wave 1 and 6.50 in Wave 3. This ordering matches the idea that structural dependence creates both vulnerability and a ready channel for rapid substitution once the shock binds, given sunk pipelines, contracts and system configuration (Sharples, 2020; Kuzemko et al., 2022). Policy signals were explicit. The Commission described a "double urgency to transform Europe's energy system" and a commitment to "end the EU's dependence on Russian fossil fuels," a frame that reoriented deployment priorities to security as well as climate (European Commission, 2022). Reports of accelerated auctions, rooftop PV roll-outs and emergency permitting support the operational channel for near-term additions (IEA, 2022). In the language of securitisation theory, the energy shock supplies the speech act and audience acceptance necessary to legitimate extraordinary prioritisation, while leaving macro constraints that temper precision in levels (Buzan, Wæver and de Wilde, 1998; Balzacq, 2005). Crucially, as practice-oriented accounts stress, securitisation turns not only on acceptance but on which audiences are positioned to authorise and implement extraordinary measures, a point that will matter for explaining cross-national differences in the Discussion (Balzacq, Léonard and Ruzicka, 2016; Balzacq, 2011). The quantitative pattern is therefore consistent with a security-driven acceleration in renewable generation rather than routine continuation, even as standard errors remind the reader that magnitudes should be interpreted with care.

6.1 Discussion – The Securitisation of Energy Policy

This discussion reads the empirical pattern through a practice-oriented account of securitisation: not simply that audiences accepted a security frame, but that specific, empowered audiences could authorise and implement extraordinary measures. In classic terms, securitisation moves an issue into a register of "existential threat, requiring emergency measures" (Buzan, Wæver and de Wilde, 1998). Practice theorists add that success depends on "a configuration of circumstances," in which actors, context and audience capacity align (Balzacq, 2005), and that what matters is not audience size but which audiences are positioned to validate and enact the claim (Balzacq, Léonard and Ruzicka, 2016). This paper's results fit that logic: the dose–response in the continuous design and the larger cohort effects for earlier and more exposed waves are consistent with security-of-supply constituencies concentrated in executive ministries, regulators and system operators being able to turn the Commission's call for a "massive speed-up and scale-up" of renewables into auctions, expedited permitting and rooftop deployment. In short, the patterns suggest securitisation as practice, where the speech act met receptive, capable audiences and translated into measurable acceleration in renewable generation.

Policy reorientation supplied the mechanism that connects the security framing to the empirical bumps in the figures. REPowerEU explicitly called for a "massive speed-up and scale-up of renewable energy" and for "rapidly reducing our dependence on Russian fossil fuels by fast-forwarding the clean transition," pairing the speech act with concrete instruments—higher targets, accelerated auctions, and expedited permitting (European Commission, 2022). The legal follow-through is visible in RED III, which raises the 2030 renewables objective to "at least 42.5%… aiming for 45%," and in the Emergency Regulation on permitting that instructs authorities to treat renewables as "overriding public interest," compressing deadlines and establishing fast-track corridors (European Commission, 2023a; European Commission, 2023b). Public opinion offered permissive consensus: Commission reporting cites that roughly 85% of respondents favoured reducing dependence on Russian gas and oil "as soon as possible," Standard Eurobarometer in 2023 finds sustained majorities for cutting Russian energy reliance, and the EIB Climate Survey records broad agreement that the war should accelerate the transition and support for stronger government action (European Commission, 2022; European Commission, 2023c; EIB, 2023). Read alongside our event-time profiles—flat leads and post-2022 divergence concentrated in high-exposure cohorts—this policy-and-audience configuration makes the results legible as security-driven acceleration rather than routine continuation, in line with accounts of structural dependence and rapid policy re-prioritisation under shock (Kuzemko et al., 2022; Sharples, 2020; Steffen and Patt, 2022).

High-exposure cohorts move first because structural dependence both tightened the constraint and expanded the political room for exceptional measures once the security frame took hold. In the data, the cohort ordering mirrors the exposure gradient documented earlier: Wave 3 comprises the most reliant states on average (about 80.6 percentage points of pre-war dependence, including Finland and Latvia), Wave 1 is also highly exposed (about 53.6, including Estonia), and Wave 2 sits in the mid-range (about 24.3, including Belgium and Germany). The corresponding effects in the staggered estimates are largest for Waves 1 and 3 and muted for Wave 2, which fits the account of "structural dependence" where pipelines, contracts and system configuration create lock-in but also "sharpen substitution incentives when a shock arrives" (Sharples, 2020; Kuzemko et al., 2022). Policy texts recognised this heterogeneity and coupled the security framing with instruments that privileged speed where needs were greatest: REPowerEU called for a "massive speed-up and scale-up of renewable energy," and the emergency permitting regulation instructed authorities to treat renewables as an "overriding public interest," compressing deadlines and enabling rapid deployment (European Commission, 2022; European Commission, 2023). Read against the event-time profiles, this is exactly where the upward breaks are most visible, suggesting that empowered security-of-supply audiences in highly exposed states could authorise and execute the acceleration (Balzacq, 2005; Balzacq, Léonard and Ruzicka, 2016).

Bulgaria is a hard case that helps clarify the mechanism. With pre-war Russian gas dependence around 93 percent and no sustained drop much below 50 percent afterward, Bulgaria sits at the top of Figure 1 but does not meet the treatment rule used in the staggered design, which requires three consecutive months at or below 10 percent after March 2022. In the Callaway and Sant'Anna set-up this places a highly exposed country in the never-treated comparison group, which likely makes the aggregated ATT conservative. In the continuous design, such extreme exposure would predict larger post-2022 gains in renewable generation, yet Bulgaria illustrates how "structural dependence" can bind in practice: sunk pipelines, long contracts, and system configuration limit the speed of substitution even when incentives are strong (Sharples, 2020; Kuzemko et al., 2022). Policy texts recognised this asymmetry and coupled the security framing with diversification and emergency-permitting tools, but the effect depends on audience capacity and institutional reach. In securitisation terms, it is not only acceptance that matters, but which audiences are positioned to authorise and execute extraordinary measures, a point that helps explain why some highly exposed states move quickly while others, like Bulgaria, adjust more slowly despite salience (Balzacq, 2005; Balzacq, Léonard and Ruzicka, 2016; European Commission, 2022).

Germany helps to clarify why system size and exposure do not map one-to-one into the same share response. In this dataset Germany sits in the medium-exposure band that defines Wave 2 (about 24.3 percentage points on average for the cohort), and the C&S estimate for Wave 2 is small and imprecise in shares (about −1.91 percentage points with a standard error near 2.1), even though Germany is the Union's largest electricity system. Read together with the continuous-treatment coefficients, this implies that Germany's counterfactual gain in renewable generation share from the security shock is moderate relative to very high-exposure cases, while absolute additions in GWh can still be large because the baseline level is high. Crucially, Figures 6c and 6d show that the cohort to which Germany belongs experiences the largest post-treatment increase in renewable generation levels, with Wave 2 overtaking Waves 1 and 3 in the GWh event-time profiles. Several compositional features help explain the muted share movement despite strong policy signals: temporary coal reactivation for security of supply, the nuclear phase-out completing in 2022, and rapid demand recovery enlarge the denominator against which renewables are measured, even as auctions and rooftop programmes expand the numerator (IEA, 2022; European Commission, 2022). The policy discourse nonetheless fits the securitisation reading. Berlin's 2022 legislative package raised the 2030 objective for renewable electricity to a much higher share and expanded auction volumes, echoing the Commission's call for a "massive speed-up and scale-up of renewable energy," which provided political cover for rapid implementation. In short, Germany's case is consistent with the results pattern: mid-range exposure yields a smaller shift in renewable generation share under the continuous and C&S designs, while policy capacity and system size still translate the security frame into sizeable absolute additions (Kuzemko et al., 2022; Steffen and Patt, 2022; Buzan, Wæver and de Wilde, 1998; Balzacq, 2005).

In sum, climate change supplied a durable rationale for clean deployment, but its incremental, long-horizon framing rarely legitimised extraordinary pace. The war reframed the same technologies as security assets, creating immediate authority for exceptional instruments, emergency permitting, and auction expansion. Publics endorsed this shift, with majorities supporting rapid reductions in Russian energy dependence, while the Commission called for a “massive speed-up and scale-up” under a “double urgency” to transform the system (European Commission, 2022; EIB, 2023). This study’s event-time breaks and cohort ordering fit a war-motivated acceleration rather than a climate-only continuation, a pattern consistent with securitisation as practice in which empowered audiences authorise urgent measures (Buzan, Wæver and de Wilde, 1998; Balzacq, 2005).

7.1 Conclusion

This study finds that the post-invasion period, although not statistically significant, coincides with a clear acceleration in renewable generation, and that the pattern is strongest where pre-war gas dependence created the sharpest security exposure. Triangulation across designs points in the same direction. The continuous treatment estimates, the dynamic profiles, and the cohort results each tell a consistent story. Placebo tests around the Green Deal do not reproduce the break. The weight of evidence therefore supports a security-driven shift rather than routine climate policy drift.

Mechanism matters. The Commission recast clean energy as a security instrument, calling for a “massive speed-up and scale-up of renewable energy” and a “double urgency to transform

Europe's energy system," while public opinion signalled consent for rapid action on Russian energy dependence. This is securitisation as practice: an authoritative speech act met receptive and empowered audiences, and those audiences translated authorization into auctions, expedited permitting, and deployment (European Commission 2022; EIB 2023; Buzan, Wæver and de Wilde 1998; Balzacq 2005; Balzacq, Léonard and Ruzicka 2016).

Scope conditions are visible. Extreme structural dependence can bind in the short run despite salience, as the Bulgarian case suggests. Large systems with mid-range exposure can register modest movements in shares while still delivering sizeable gains in absolute generation, as the German case indicates. Audience composition helps to explain these contrasts: outcomes turn on which ministries, regulators and system operators are positioned to authorize and implement exceptional measures, not on diffuse acceptance alone.

Limits remain. The post window is short, level estimates are imprecise, and unobserved shocks cannot be ruled out entirely. Even so, convergence across designs and the placebo contrast give the main claim resilience. Policy should retain the instruments that delivered speed, while restoring deliberative safeguards as crisis ebbs. Theoretically, the contribution is to show how audience configuration mediates securitisation in energy transitions, turning a security frame into measurable acceleration in renewable generation.

Bibliography

Abadie, A., Athey, S., Imbens, G. and Wooldridge, J.M. (2023) 'When Should You Adjust Standard Errors for Clustering?', Quarterly Journal of Economics, 138(1), pp. 1–35.

Albert, M. (2022) 'Climate emergency and securitization politics: towards a climate politics of the extraordinary', *Globalizations*, 19(8), pp. 1212–1226. https://doi.org/10.1080/14747731.2022.2117501.

Angrist, J.D. and Pischke, J.-S. (2009) *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton: Princeton University Press. https://doi.org/10.2307/j.ctvcm4j72.

Angrist, J.D. and Pischke, J.-S. (2010) 'The credibility revolution in empirical economics: how better research design is taking the con out of econometrics', *Journal of Economic Perspectives*, 24(2), pp. 3–30. https://doi.org/10.1257/jep.24.2.3.

Arkhangelsky, D., Athey, S., Hirshberg, D., Imbens, G.W. and Wager, S. (2021) 'Synthetic difference-in-differences', *American Economic Review*, 111(12), pp. 4088–4118. https://doi.org/10.1257/aer.20191359.

Athey, S. and Imbens, G.W. (2017) 'The state of applied econometrics: causality and policy evaluation', *Journal of Economic Perspectives*, 31(2), pp. 3–32. https://doi.org/10.1257/jep.31.2.3.

Baker, A., Larcker, D.F. and Wang, C.C.Y. (2022) 'How much should we trust staggered difference-in-differences estimates?', *Journal of Financial Economics*, 144(2), pp. 370–395. https://doi.org/10.1016/j.jfineco.2021.05.008.

Baker, A., Callaway, B., Cunningham, S., Goodman-Bacon, A. and Sant'Anna, P.H.C. (2025) 'Difference-in-Differences Designs: A Practitioner's Guide', arXiv preprint.

Balzacq, T. (2005) 'The three faces of securitization: Political agency, audience and context', *European Journal of International Relations*, 11(2), pp. 171–201. https://doi.org/10.1177/1354066105052960.

Balzacq, T. (2011) *Securitization Theory: How Security Problems Emerge and Dissolve*. London: Routledge.

Balzacq, T., Léonard, S. and Ruzicka, J. (2016) '"Securitization" revisited: Theory and cases', *International Relations*, 30(4), pp. 494–531. https://doi.org/10.1177/0047117815596590.

Bertrand, M., Duflo, E. and Mullainathan, S. (2004) 'How much should we trust Differences-in-Differences estimates?', *Quarterly Journal of Economics*, 119(1), pp. 249–275. https://doi.org/10.1162/003355304772839588.

Bridge, G. (2015) 'Energy (in)security: world-making in an age of scarcity', *Geographical Journal*, 181(4), pp. 328–339. https://doi.org/10.1111/geoj.12114.

Bridge, G. and Bradshaw, M. (2022) 'Rethinking energy materialities in the shadow of Russia's war on Ukraine', *Energy Research & Social Science*, 94, p. 102868. https://doi.org/10.1016/j.erss.2022.102868.

Bridge, G., Bouzarovski, S., Bradshaw, M. and Eyre, N. (2013) ‘Geographies of energy transition: Space, place and the low-carbon economy’, *Energy Policy*, 53, pp. 331–340. https://doi.org/10.1016/j.enpol.2012.10.066.

Bueno de Mesquita, E. and Fowler, A. (2021) *Thinking clearly with data : a guide to quantitative reasoning and analysis*. Princeton: Princeton University Press.

Buzan, B., Wæver, O. and de Wilde, J. (1998) *Security: A New Framework for Analysis*. Boulder, CO: Lynne Rienner.

Callaway, B. and Sant’Anna, P.H.C. (2021) ‘Difference-in-Differences with multiple time periods’, *Journal of Econometrics*, 225(2), pp. 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001.

Callaway, B., Goodman-Bacon, A. and Sant’Anna, P.H.C. (2025) ‘Difference-in-Differences with a Continuous Treatment’. Available at: https://doi.org/10.48550/arxiv.2107.02637.

Cameron, A.C. and Miller, D.L. (2015) ‘A practitioner’s guide to cluster-robust inference’, *Journal of Human Resources*, 50(2), pp. 317–372. https://doi.org/10.3368/jhr.50.2.317.

Carney, M. (2015) ‘Breaking the tragedy of the horizon – climate change and financial stability’, Speech given at Lloyd’s of London, 29 September. Bank of England.

Chatham House (2021) ‘Building global climate security’, *Expert Comment*, 29 September. London: Chatham House.

Cherp, A. and Jewell, J. (2014) ‘The concept of energy security: Beyond the four As’, *Energy Policy*, 75, pp. 415–421. https://doi.org/10.1016/j.enpol.2014.09.005.

Christensen, G. and Miguel, E. (2018) ‘Transparency, reproducibility, and the credibility of economics research’, *Journal of Economic Literature*, 56(3), pp. 920–980. https://doi.org/10.1257/jel.20171350.

Cullum, R. (2024) ‘Making a world of climate insecurity: The threat multiplier frame and the U.S. national security community’, *Global Studies Quarterly*, 4(4), p. ksad029. https://doi.org/10.1093/isagsq/ksad029.

Cunningham, S. (2021) *Causal Inference: The Mixtape*. New Haven: Yale University Press. https://doi.org/10.12987/9780300255881.

de Chaisemartin, C., D’Haultfœuille, X. and Vazquez-Bare, G. (2024) ‘Difference-in-Difference Estimators with Continuous Treatments and No Stayers’, AEA Papers and Proceedings, 114, pp. 610–613.

de Chaisemartin, C., D’Haultfœuille, X., Pasquier, F., Sow, D. and Vazquez-Bare, G. (2025) ‘Difference-in-Differences Estimators for Treatments Continuously Distributed at Every Period’, arXiv preprint arXiv:2201.06898.

Dalby, S. (2013) ‘The geopolitics of climate change’, *Political Geography*, 37, pp. 38–47. https://doi.org/10.1016/j.polgeo.2013.09.004.

de Chaisemartin, C. and D’Haultfœuille, X. (2020) ‘Two-way fixed effects estimators with heterogeneous treatment effects’, *American Economic Review*, 110(9), pp. 2964–2996. https://doi.org/10.1257/aer.20181169.

Dryzek, J.S. (2016) ‘Reframing the problem of climate change: From zero sum game to win–win solutions by Hans Joachim Schellnhuber et al.’, *Environmental Politics*, 25(5), pp. 890–892. https://doi.org/10.1080/09644016.2016.1189232.

Dupont, C. and Oberthür, S. (2021) 'The European Green Deal after COVID-19: Building economic recovery and ecological transition', *Politics and Governance*, 9(3), pp. 90–100. https://doi.org/10.17645/pag.v9i3.4320.

European Commission (2018) *Special Eurobarometer 484: Environment.* Brussels: European Union.

European Commission (2019a) *Special Eurobarometer 497: Climate change.* Brussels: European Union.

European Commission (2019b) *The European Green Deal. Communication from the Commission, COM(2019) 640 final, 11 December.* Brussels: European Commission.

European Commission (2021) *Special Eurobarometer 513: Climate change.* Brussels: European Union.

European Commission (2022a) *Special Eurobarometer 527: Climate change.* Brussels: European Union.

European Commission (2022b) *REPowerEU Plan. Communication from the Commission, COM(2022) 230 final, 18 May.* Brussels: European Commission.

European Commission (2023) *Standard Eurobarometer 99 – Public opinion in the European Union.* Brussels: European Union.

European Commission (2024) *Eurobarometer – EU Challenges and Priorities, July 2024.* Brussels: European Union.

European Commission (2025) *Special Eurobarometer 565: Public perceptions on climate change and the transition.* Brussels: European Union.

European Investment Bank (2023) *EIB Climate Survey 2022–2023*. Luxembourg: EIB.

Eurostat (2022) *Quality report of European Union statistics on electricity and natural gas*. Luxembourg: Publications Office of the European Union.

Falkner, R. (2023) 'Weaponised energy and climate change: assessing Europe's response to the Ukraine war', *LSE Public Policy Review*, 3(1), p. 10. https://doi.org/10.31389/lseppr.78.

Farrell, H. and Newman, A.L. (2019) 'Weaponized interdependence: How global economic networks shape state coercion', *International Security*, 44(1), pp. 42–79. https://doi.org/10.1162/isec_a_00351.

Fearon, J.D. (1995) 'Rationalist explanations for war', *International Organization*, 49(3), pp. 379–414. https://doi.org/10.1017/S0020818300033324.

Floyd, R. (2019) *The Morality of Security: A Theory of Just Securitization*. Cambridge: Cambridge University Press.

Floyd, R. and Croft, S. (eds.) (2011) *Securitisation Theory: A New Framework for Analysis*. Abingdon: Routledge.

Fu, Q., Chen, Y.E., Jang, C.-L. and Chang, C.-P. (2021) 'The impact of international sanctions on environmental performance', *Science of the Total Environment*, 745, p. 141007. https://doi.org/10.1016/j.scitotenv.2020.141007.

Geels, F.W. (2014) 'Regime resistance against low-carbon transitions: Introducing politics and power into the multi-level perspective', *Theory, Culture & Society*, 31(5), pp. 21–40. https://doi.org/10.1177/0263276414531627.

Geels, F.W., Sovacool, B.K., Schwanen, T. and Sorrell, S. (2017) 'Sociotechnical transitions for deep decarbonization', *Science*, 357(6357), pp. 1242–1244. https://doi.org/10.1126/science.aao3760.

Goldthau, A. (2014) 'Rethinking the governance of energy infrastructure: Scale, decentralization and polycentrism', *Energy Research & Social Science*, 1, pp. 134–140. https://doi.org/10.1016/j.erss.2014.02.009.

Goodman-Bacon, A. (2021) 'Difference-in-Differences with variation in treatment timing', *Journal of Econometrics*, 225(2), pp. 254–277. https://doi.org/10.1016/j.jeconom.2021.03.014.

Haddad, M.F.C., Huber, M. and Zhang, L.Z. (2024) 'Difference-in-Differences with Time-varying Continuous Treatments using Double/Debiased Machine Learning', arXiv preprint.

Henderson, J. (2014) 'The role of natural gas in the Russia–Ukraine crisis', *Oxford Energy Comment*. Oxford: Oxford Institute for Energy Studies.

Huang, Y., Marin, G. and Vona, F. (2022) 'The impact of the EU Emissions Trading System on firm productivity and employment: Evidence from a transition economy', *Energy Economics*, 105, p. 105716. https://doi.org/10.1016/j.eneco.2021.105716.

International Energy Agency (IEA) (2022) *Renewables 2022: Analysis and forecast to 2027*. Paris: IEA.

International Energy Agency (IEA) and Eurostat (2020) *Energy Statistics Manual*. Paris: OECD/IEA.

Jaeger, C.C., Hasselmann, K., Leipold, G., Mangalagiu, D. and Tàbara, J.D. (2015) *Reframing the Problem of Climate Change: From Zero-Sum Game to Win–Win Solutions*. Abingdon: Routledge.

Kahn-Lang, A. and Lang, K. (2020) 'The promise and pitfalls of differences-in-differences: Reflections on 16 and Pregnant and other applications', *Journal of Business & Economic Statistics*, 38(3), pp. 613–620. https://doi.org/10.1080/07350015.2018.1546591.

Kellstedt, P.M. and Whitten, G.D. (2018) *The Fundamentals of Political Science Research* (3rd ed.). Cambridge: Cambridge University Press. https://doi.org/10.1017/9781108131704.

Kuzemko, C., Blondeel, M., Dupont, C., Brisbois, M.C., Huang, Y., Jenkins, K., Skovgaard, J., Szulecki, K., van de Graaf, T. and Weko, S. (2022) 'Russia's war on Ukraine, European energy policy responses & implications for sustainable transformations', *Energy Research & Social Science*, 93, p. 102842. https://doi.org/10.1016/j.erss.2022.102842.

Maliszewska-Nienartowicz, J. (2024) 'Impact of Russia's invasion of Ukraine on renewable energy development in Germany and Italy', *Utilities Policy*, 87, p. 101731. https://doi.org/10.1016/j.jup.2024.101731.

McDonald, M. (2018) 'Climate change and security: Towards ecological security?', *International Theory*, 10(2), pp. 153–180. https://doi.org/10.1017/S1752971918000069.

McWilliams, B., Tagliapietra, S. and Zachmann, G. (2025) 'Europe's energy information problem', *Bruegel Policy Brief*, No. 07/2025. Brussels: Bruegel

Meadowcroft, J. (2011) 'Engaging with the politics of sustainability transitions', *Environmental Innovation and Societal Transitions*, 1(1), pp. 70–75. https://doi.org/10.1016/j.eist.2011.02.003.

Miguel, E. and Roland, G. (2011) 'The long-run impact of bombing Vietnam', *Journal of Development Economics*, 96(1), pp. 1–15. https://doi.org/10.1016/j.jdeveco.2010.08.006.

Munck af Rosenschöld, J., Rozbicka, P. and Lanér, D. (2014) 'Institutional inertia and climate change: a new institutionalist perspective', *Wiley Interdisciplinary Reviews: Climate Change*, 5(5), pp. 617–628. https://doi.org/10.1002/wcc.292.

Oberthür, S. and Dupont, C. (2021) 'The European Union's international climate leadership: Towards a grand climate strategy?', *Journal of European Public Policy*, 28(7), pp. 1095–1114. https://doi.org/10.1080/13501763.2021.1918218.

Roth, J., Sant'Anna, P.H.C., Bilinski, A. and Poe, J. (2023) 'What's trending in difference-in-differences? A synthesis of the recent econometrics literature', *Journal of Econometrics*, 236(2), pp. 145–162.

Rothe, D., Hentschel, C. and Schröder, U. (2025) 'Recomposing the climate–security nexus: A conceptual introduction', *Geoforum*, 159, p. 104195. https://doi.org/10.1016/j.geoforum.2024.104195.

Sadorsky, P. (2019) 'Assessing the missing data problem in panel energy research', *Energy Policy*, 134, p. 110953. https://doi.org/10.1016/j.enpol.2019.110953.

Sharples, J. (2020) 'Russia's political discourse on the EU's energy transition (2014–2019)', *Energy Policy*, 144, p. 111692. https://doi.org/10.1016/j.enpol.2020.111692.

Simonis, U.E. (2012) 'Reframing the problem of climate change: from zero sum game to win–win solutions', *Environmental Politics*, 21(6), pp. 1016–1017. https://doi.org/10.1080/09644016.2012.724240.

Sovacool, B.K. (2011) 'Evaluating energy security in the Asia Pacific: Towards a more comprehensive approach', *Energy Policy*, 39(11), pp. 7472–7479. https://doi.org/10.1016/j.enpol.2010.12.009.

Steffen, B. and Patt, A. (2022) 'A historical turning point? Early evidence on how the Russia–Ukraine war changes public support for clean energy policies', *Energy Research & Social Science*, 91, p. 102758. https://doi.org/10.1016/j.erss.2022.102758.

Stern, D.I. (2018) 'Energy and economic growth', in Fouquet, R. (ed.) *Handbook on Green Growth*. Cheltenham: Edward Elgar, pp. 67–84. https://doi.org/10.4337/9781788110686.00011.

Stritzel, H. (2007) 'Towards a theory of securitization: Copenhagen and beyond', *European Journal of International Relations*, 13(3), pp. 357–383. https://doi.org/10.1177/1354066107080128.

Sun, L. and Abraham, S. (2021) 'Estimating dynamic treatment effects in event studies with heterogeneous treatment effects', *Journal of Econometrics*, 225(2), pp. 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006.

Szulecki, K. and Overland, I. (2023) 'Russian nuclear energy diplomacy and its implications for energy security in the context of the war in Ukraine', *Nature Energy*, 8(4), pp. 413–421. https://doi.org/10.1038/s41560-023-01228-5.

Tagliapietra, S. and Zachmann, G. (2022) 'Europe's energy crisis and the Green Deal: a reality check', *Nature Energy*, 7(10), pp. 844–846. https://doi.org/10.1038/s41560-022-01135-6.

Trombetta, M.J. (2008) 'Environmental security and climate change: Analysing the discourse', *Cambridge Review of International Affairs*, 21(4), pp. 585–602. https://doi.org/10.1080/09557570802452920.

United Nations Intergovernmental Panel on Climate Change (IPCC) (2022) *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the IPCC*. Cambridge: Cambridge University Press. https://doi.org/10.1017/9781009157926.

Unruh, G.C. (2000) 'Understanding carbon lock-in', *Energy Policy*, 28(12), pp. 817–830. https://doi.org/10.1016/S0301-4215(00)00070-7.

Vezzoni, R. (2023) 'Green growth for whom, how and why? The REPowerEU plan and the inconsistencies of European Union energy policy', *Energy Research & Social Science*, 101, p. 103134. https://doi.org/10.1016/j.erss.2023.103134.

Vogler, A. (2023) 'How national security strategies frame climate and environmental change as security issues: a global comparative content analysis (2000–2020)', *Political Geography*, 105, p. 102893. https://doi.org/10.1016/j.polgeo.2023.102893.

Voigt, C. (2019) 'The potential and limits of climate litigation', *Transnational Environmental Law*, 8(2), pp. 229–245. https://doi.org/10.1017/S2047102519000057.

von der Leyen, U. (2019) *A Union that strives for more: My agenda for Europe. Political Guidelines for the next European Commission 2019–2024*. Brussels: European Commission.

von Homeyer, I., Oberthür, S. and Dupont, C. (2025) 'EU climate policy in turbulent times: Understanding the response to the Covid-19 pandemic and Russia's full-scale invasion of Ukraine', *Environmental Politics* (early online). https://doi.org/10.1080/09644016.2025.2432190.

Warner, J. and Boas, I. (2019) *Securitisation of Climate Change: Actors, Processes and Consequences*. Abingdon: Routledge.

Wendt, A. (1992) 'Anarchy is what states make of it: the social construction of power politics', *International Organization*, 46(2), pp. 391–425. https://doi.org/10.1017/S0020818300027764.

Wolf, S., Teitge, J., Mielke, J., Schütze, F. and Jaeger, C. (2021) 'The European Green Deal – more than climate neutrality', *Intereconomics*, 56(2), pp. 99–107. https://doi.org/10.1007/s10272-021-0963-z.

Yang, X., Cui, W., Yang, X., Yang, Y., Zhuang, L. and Zhang, L. (2025) 'Europe's energy transition is accelerated by the Russia–Ukraine war: A novel assessment based on two scenario simulations', *Renewable Energy*, 255, p. 121226. https://doi.org/10.1016/j.renene.2022.121226.

Yergin, D. (2006) 'Ensuring energy security', *Foreign Affairs*, 85(2), pp. 69–82. https://doi.org/10.2307/20031912.

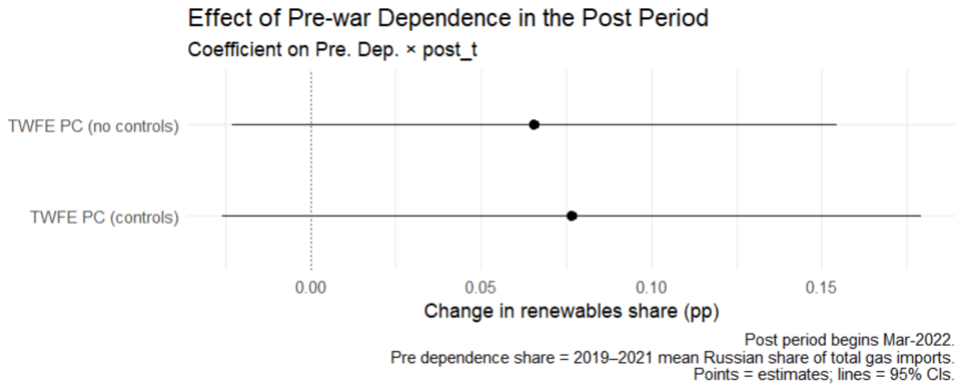
York, R. (2012) 'Do alternative energy sources displace fossil fuels?', *Nature Climate Change*, 2(6), pp. 441–443. https://doi.org/10.1038/nclimate1451.

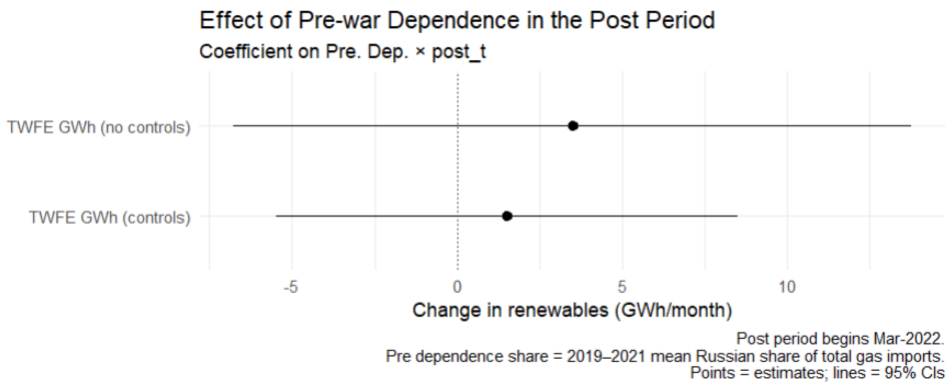
Youngs, R. (2014) *Climate Change and European Security*. Abingdon: Routledge.

Annex 1 - Data

Data	Unit of Measure	SIEC (Energy Product)	Balances / Flow	Partner/Geo	Notes	Coverage
estat_demo_pjan	Male + Female All ages	N/A	Population Full value	EU27	Annual population by country	2018 - 2024
estat_nama_10_pc	Purchasing Power Standard (PPS) per capita	N/A	GDP per capita (constant PPS)	EU27	Annual GDP per capita (PPS)	2018 - 2024
estat_nrg_bal_c	Gigawatt hours (GWh)	C0000X0350-0370 G3000 O4000XBIO TOTAL	Gross Inland Consumption (GIC)	EU27	Annual fossil fuel balances	2018 - 2024
estat_nrg_cb_gasm	Gigawatt hours (GWh)	G3000	Inland Consumption – observed (IC-OBS)	EU27	Monthly natural gas consumption	Jan 2018 – Mar 2025
estat_nrg_cb_pem	Gigawatt hours (GWh)	RA100, RA110 RA120, RA200 RA300, RA310 RA320, RA400 RA410, RA420 RA500_5160	Primary energy production	EU27	Monthly renewable energy production (absolute, GWh)	Jan 2018 – Mar 2025
estat_nrg_cb_pem	Percentage (%)	RA100, RA110 RA120, RA200 RA300, RA310 RA320, RA400 RA410, RA420 RA500_5160	Primary energy production share	EU27	Monthly renewable energy share (%)	Jan 2018 – Mar 2025
estat_nrg_cb_sffm	Thousand tonnes (THS_T)	C0100	Gross Inland Deliveries - Observed (GID_OBS)	EU27	Monthly solid fossil fuels supply	Jan 2018 – Mar 2025
estat_nrg_stk_gasm	Million cubic meters (MIO_M3)	G3000	Closing stock - national territory (STKCL_NAT)	EU27	Monthly gas storage levels	Jan 2018 – Mar 2025
estat_nrg_ti_gasm	Million cubic meters (MIO_M3)	G3000 G3200	Imports	RU (Russia)/ EU27	Monthly gas imports from Russia	Jan 2018 – Mar 2025
estat_nrg_ti_gasm	Million cubic meters (MIO_M3)	G3000 G3200	Imports	TOTAL/ EU27	Monthly total gas imports (all partners)	Jan 2018 – Mar 2025

Figure Xa - Xd. TWFE (pre/post)





Annex 2 - Code

```
#install.packages( c("parallelly","globals","listenv","future","future.apply","recipes","tidyverse","slider", "lubridate","fixest","did","marginaleffects"),  dependencies = TRUE)

# ==================================================================================
#                 Prep: Libraries & Functions
# ==================================================================================
library(parallelly)
library(future)
library(future.apply)
library(recipes)
library(tidyverse)
library(slider)
library(lubridate)
library(fixest)
library(did)
library(marginaleffects)
library(ggplot2)

```

```
set.seed(123)

# Because there were some issues with dates in TSV files being character I tried
# to standardize the process
# CY - Cyprus removed entirely due to data issues

# ------------------------
#  MONTHLY FUNCTION HELPERS
# ------------------------


# Date helper function
as_month_date <- function(x) {
  x <- as.character(x)
  out <- ifelse(grepl("^\\d{4}-\\d{2}$", x), paste0(x, "-01"),
                ifelse(grepl("^\\d{6}$", x), paste0(substr(x,1,4), "-",
                substr(x,5,6), "-01"), NA_character_))
  as.Date(out)
}

# Pivot helper function
pivot_monthly <- function(df, id_cols) {
  df %>%
    pivot_longer(cols = -all_of(id_cols), names_to = "date_chr", values_to = "value") %>%
```

```
    mutate(date = as_month_date(date_chr)) %>%
    select(-date_chr)%>%
    filter(country != "CY")
}

# -------------------------
# YEARLY FUNCTION HELPERS
# -------------------------

as_year_date <- function(x) {
  yr <- str_extract(as.character(x), "\\d{4}")
  as.Date(paste0(yr, "-01-01"))
}

# Pivot helper function
pivot_long_year <- function(df, id_cols) {
  df %>%
    pivot_longer(cols = matches("^\\d{4}$"),
                 names_to = "year", values_to = "value") %>%
    mutate(date = as_year_date(year)) %>%
    select(-year)%>%
    filter(country != "CY")
}

```

```
# ================================================================================
#                    MONTHLY DATA
# ================================================================================

# -------------------------
#      RENEWABLES
#    Percentage (PC)
# -------------------------
raw_PC <- read_tsv("estat_nrg_cb_pem_filtered_PC.tsv", show_col_types = FALSE)

cleaned_PC <- raw_PC %>%
  separate(col = 1, into = c("freq", "siec", "unit", "country"), sep = ",") %>%
  filter(siec %in% c("RA100","RA110","RA120","RA200","RA300","RA310","RA320","RA400","RA410","RA420","RA500_5160"))

long_PC <- pivot_monthly(cleaned_PC, id_cols = c("freq","siec","unit","country")) %>%
  mutate(value = as.numeric(na_if(value, ":")))

renew_PC <- long_PC %>%
```

```
  pivot_wider(names_from = siec, values_from = value, names_prefix = "nrg_cb_pem_") %>%
  select(-freq, -unit) %>%
  rename(
    Hydro_Total_PC     = nrg_cb_pem_RA100,
    Hydro_Pure_PC      = nrg_cb_pem_RA110,
    Hydro_Mixed_PC     = nrg_cb_pem_RA120,
    Geothermal_PC      = nrg_cb_pem_RA200,
    Wind_Total_PC      = nrg_cb_pem_RA300,
    Wind_Onshore_PC    = nrg_cb_pem_RA310,
    Wind_Offshore_PC   = nrg_cb_pem_RA320,
    Solar_Total_PC     = nrg_cb_pem_RA400,
    Solar_Thermal_PC   = nrg_cb_pem_RA410,
    Solar_PV_PC        = nrg_cb_pem_RA420,
    Other_Renewables_PC = nrg_cb_pem_RA500_5160
  ) %>%
  mutate(Total_Renewables_PC = rowSums(across(c(Hydro_Total_PC, Geothermal_PC, Wind_Total_PC, Solar_Total_PC, Other_Renewables_PC)), na.rm = TRUE))

# -------------------------
#        RENEWABLES
#          (GWh)
# -------------------------
```

```
raw_GWH <- read_tsv("estat_nrg_cb_pem_filtered_GWH.tsv", show_col_types = FALSE)

cleaned_GWH <- raw_GWH %>%
  separate(col = 1, into = c("freq", "siec", "unit", "country"), sep = ",") %>%
  filter(siec %in% c("RA100","RA110","RA120","RA200",
                     "RA300","RA310","RA320","RA400","RA410","RA420","RA500_5160"))

long_GWH <- pivot_monthly(cleaned_GWH, id_cols = c("freq","siec","unit","country")) %>%
  mutate(value = as.numeric(na_if(value, ":")))

renew_GWH <- long_GWH %>%
  pivot_wider(names_from = siec, values_from = value, names_prefix = "nrg_cb_pem_") %>%
  select(-freq, -unit) %>%
  rename(
    Hydro_Total_GWH      = nrg_cb_pem_RA100,
    Hydro_Pure_GWH       = nrg_cb_pem_RA110,
    Hydro_Mixed_GWH      = nrg_cb_pem_RA120,
    Geothermal_GWH       = nrg_cb_pem_RA200,
    Wind_Total_GWH       = nrg_cb_pem_RA300,
    Wind_Onshore_GWH     = nrg_cb_pem_RA310,
    Wind_Offshore_GWH    = nrg_cb_pem_RA320,
```

```
    Solar_Total_GWH      = nrg_cb_pem_RA400,
    Solar_Thermal_GWH    = nrg_cb_pem_RA410,
    Solar_PV_GWH         = nrg_cb_pem_RA420,
    Other_Renewables_GWH = nrg_cb_pem_RA500_5160
  ) %>%
  mutate(Total_Renewables_GWH = rowSums(across(c(Hydro_Total_GWH, Geothermal_GWH,
                                                  Wind_Total_GWH, Solar_Total_GWH,
                                                  Other_Renewables_GWH)), na.rm = TRUE))

# -------------------------
#    GAS IMPORTS TOTAL
#       (NG + LNG)
# -------------------------
raw_total_gas <- read_tsv("estat_nrg_ti_gasm_filtered_Total.tsv", col_types = cols(.default = "c"), show_col_types = FALSE)

cleaned_total_gas <- raw_total_gas %>%
  separate(col = 1, into = c("freq","siec","partner","unit","country"), sep = ",") %>%
  filter(siec %in% c("G3000","G3200"))

# Monthly column names to YYYY-MM
date_cols_total <- setdiff(names(cleaned_total_gas), c("siec","partner","country","freq","unit"))
new_names_total <- vapply(date_cols_total, function(x){
```

```
  if (str_detect(x, "^\\\
\\d{6}$")) format(as.Date(paste0(x, "01"), "%Y%m%d"), "%Y-%m") else x
}, character(1))
names(cleaned_total_gas)[match(date_cols_total, names(cleaned_total_gas))] <- new_names_total

long_total <- pivot_monthly(cleaned_total_gas, id_cols = c("freq","siec","partner","unit","country")) %>%
  mutate(value = as.numeric(na_if(value, ":")))

final_total <- long_total %>%
  select(-partner, -unit, -freq) %>%
  pivot_wider(names_from = siec, values_from = value, names_prefix = "nrg_cb_pem_") %>%
  rename(NG_mcm_total = nrg_cb_pem_G3000,
         LNG_mcm_total = nrg_cb_pem_G3200) %>%
  mutate(agg_total_imports = rowSums(across(c(NG_mcm_total, LNG_mcm_total)), na.rm = TRUE))

# -------------------------
#    GAS IMPORTS RUSSIA
#        (NG + LNG)
# -------------------------
raw_ru_gas <- read_tsv("estat_nrg_ti_gasm_filtered_Russia.tsv", col_types = cols(.default = "c"), show_col_types = FALSE)
```

```r

cleaned_ru_gas <- raw_ru_gas %>%
  separate(col = 1, into = c("freq","siec","partner","unit","country"), sep = ",") %>%
  filter(siec %in% c("G3000","G3200"))

date_cols_ru <- setdiff(names(cleaned_ru_gas), c("siec","partner","country","freq","unit"))
new_names_ru <- vapply(date_cols_ru, function(x){
  if (str_detect(x, "^\\d{6}$")) format(as.Date(paste0(x, "01"), "%Y%m%d"), "%Y-%m") else x
}, character(1))
names(cleaned_ru_gas)[match(date_cols_ru, names(cleaned_ru_gas))] <- new_names_ru

long_ru <- pivot_monthly(cleaned_ru_gas, id_cols = c("freq","siec","partner","unit","country")) %>%
  mutate(value = as.numeric(na_if(value, ":")))

final_ru <- long_ru %>%
  select(-partner, -unit, -freq) %>%
  pivot_wider(names_from = siec, values_from = value, names_prefix = "nrg_cb_pem_") %>%
  rename(NG_mcm_RU = nrg_cb_pem_G3000,
      LNG_mcm_RU = nrg_cb_pem_G3200) %>%
```

```
 mutate(agg_RU_imports = rowSums(across(c(NG_mcm_RU, LNG_mcm_RU)), na.rm = TRUE))

# ------------------------
#        GAS
#    CONSUMPTION
# ------------------------
raw_gas_cons <- read_tsv("estat_nrg_cb_gasm_filtered_cons.tsv", col_types = cols(.default = "c"), show_col_types = FALSE)

cleaned_gas_cons <- raw_gas_cons %>%
 separate(col = 1, into = c("freq","nrg_bal","siec","unit","country"), sep = ",") %>%
 select(-freq, -unit, -nrg_bal)

long_gas_cons <- pivot_monthly(cleaned_gas_cons, id_cols = c("siec","country")) %>%
 mutate(gas_consumption_mcm = as.numeric(na_if(value, ":"))) %>%
 select(country, date, gas_consumption_mcm)

# ------------------------
#        COAL
#    CONSUMPTION
# ------------------------
raw_coal <- read_tsv("estat_nrg_cb_sffm_filtered.tsv", col_types = cols(.default = "c"), show_col_types = FALSE)
```

```
cleaned_coal <- raw_coal %>%
  separate(col = 1, into = c("freq","nrg_bal","siec","unit","country"), sep = ",") %>%
  select(-freq, -unit, -nrg_bal)

long_coal <- pivot_monthly(cleaned_coal, id_cols = c("siec","country")) %>%
  mutate(coal_consumption_tht = as.numeric(na_if(value, ":"))) %>%
  select(country, date, coal_consumption_tht)

# ------------------------
#          GAS
#     STOCKS/Storage
# ------------------------
raw_stocks <- read_tsv("estat_nrg_stk_gasm_filtered.tsv", col_types = cols(.default = "c"), show_col_types = FALSE)

cleaned_stocks <- raw_stocks %>%
  separate(col = 1, into = c("freq","stk_flow","siec","unit","country"), sep = ",") %>%
  select(-freq, -unit, -stk_flow)

long_stocks <- pivot_monthly(cleaned_stocks, id_cols = c("siec","country")) %>%
  mutate(gas_stock_mcm = as.numeric(na_if(value, ":"))) %>%
  select(country, date, gas_stock_mcm)

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

```
#       MERGE DATA
# -------------------------
merged_data <- renew_PC %>%
  full_join(renew_GWH,  by = c("country","date")) %>%
  full_join(final_total, by = c("country","date")) %>%
  full_join(final_ru,    by = c("country","date")) %>%
  full_join(long_gas_cons, by = c("country","date")) %>%
  full_join(long_coal,     by = c("country","date")) %>%
  full_join(long_stocks,   by = c("country","date")) %>%
  arrange(country, date)

# Russian import dependency (%)
merged_data <- merged_data %>%
  mutate(
    Russia_dependency_pct = case_when(
      is.na(agg_total_imports) | agg_total_imports == 0 ~ NA_real_,
      TRUE ~ (agg_RU_imports / agg_total_imports) * 100
    ),
    Russia_dependency_pct = round(pmin(Russia_dependency_pct, 100), 2),
  )

# -------------------------
#    C&S Treatment flagging
#  >10% for 3 cons. months
# -------------------------
```

```
# Parameters
τ        <- 0.10                    # Threshold
K        <- 3                       # consecutive months
min_total <- 1                      # minimum total imports
min_start <- as.Date("2022-03-01")       # earliest treatment

# Pre-war dependency share (up to 02-2022)
pre_cut <- min_start
prewar_avg <- merged_data %>%
  filter(date < pre_cut) %>%
  mutate(
    pre_ru_share = if_else(!is.na(agg_total_imports) & agg_total_imports >= min_total,
                           agg_RU_imports / agg_total_imports, NA_real_)
  ) %>%
  group_by(country) %>%
  summarise(pre_dep_share = mean(pre_ru_share, na.rm = TRUE), .groups = "drop")


# Treatment based on dependency
merged_data <- merged_data %>%
  left_join(prewar_avg, by = "country") %>%
  arrange(country, date) %>%
  group_by(country) %>%
  mutate(
```

```
    ru_share = if_else(!is.na(agg_total_imports) & agg_total_imports >= min_total, # Current month’s RU share
                       agg_RU_imports / agg_total_imports, NA_real_),
    low      = !is.na(ru_share) & (ru_share <= τ), # Flag months where RU share is ≤ τ
    nonmiss_k = slide_int(!is.na(ru_share), ~ sum(.x), .before = K - 1, .after = 0, .complete = TRUE), # accounts for missing data K-month window
    all_low_k = slide_lgl(low, ~ all(.x), .before = K - 1, .after = 0, .complete = TRUE), # Are all K months low?
    eligible = !is.na(pre_dep_share) & (pre_dep_share > τ), # Accounts for countries with no or negligible amounts of imports pre war
    cutoff_hit = eligible & (nonmiss_k == K) & all_low_k & (date >= min_start), # Cutoff hits only if eligible, meets K-month low condition, and date is after min_start
    first_treat_date = if (any(cutoff_hit, na.rm = TRUE)) min(date[cutoff_hit]) else as.Date(NA) # First month of sustained dependency cut-off
  ) %>%
  ungroup() %>%
  mutate(
    treat = if_else(!is.na(first_treat_date) & date >= first_treat_date, 1L, 0L),# Treatment indicator... once treated, always treated
    # Group and time identifiers for C&S
    tname = year(date) * 100L + month(date),
    gname = if_else(is.na(first_treat_date), 0L,
                    year(first_treat_date) * 100L + month(first_treat_date)),
    event_time = if_else(is.na(first_treat_date), NA_integer_,
                         (year(date) - year(first_treat_date)) * 12L +
```

```
                    (month(date) - month(first_treat_date)))
  )
# -------------------------
# Export SINGLE merged CSV
# -------------------------
write_csv(merged_data, "merged_monthly_energy_dataset.csv")

# ==============================================================================
#                        YEARLY DATA
# ==============================================================================

# -------------------------
#       POPULATION
# -------------------------
raw_pop <- read_tsv("estat_demo_pjan_filtered.tsv",
                    col_types = cols(.default = "c"))

pop_data <- raw_pop %>%
  separate(col = 1,
           into = c("freq", "unit", "age", "sex", "country"),
           sep = ",") %>%
```

```
  filter(age == "TOTAL", sex == "T") %>%
  select(-freq, -unit, -age, -sex) %>%
  pivot_long_year(id_cols = c("country")) %>%
  mutate(population = as.numeric(na_if(str_replace_all(value, "[a-z]", ""), ":"))) %>%
  select(country, date, population)

# -------------------------
#           GDP
#        PER CAPITA (PPS)
# -------------------------
raw_gdp <- read_tsv("estat_nama_10_pc_filtered.tsv",
                    col_types = cols(.default = "c"))

gdp_data <- raw_gdp %>%
  separate(col = 1,
           into = c("freq", "unit", "na_item", "country"),
           sep = ",") %>%
  filter(na_item == "B1GQ") %>%
  select(-freq, -unit, -na_item) %>%
  pivot_long_year(id_cols = c("country")) %>%
  mutate(gdp_pc_pps = as.numeric(na_if(str_replace_all(value, "[a-z]", ""), ":"))) %>%
  select(country, date, gdp_pc_pps)

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

```
#      FOSSIL FUEL
#    SHARE OF ENERGY MIX
# -------------------------
raw_energy <- read_tsv("estat_nrg_bal_c_filtered.tsv",
                       col_types = cols(.default = "c"))

cleaned_mix <- raw_energy %>%
  separate(col = 1,
           into = c("freq", "nrg_bal", "siec", "unit", "country"),
           sep = ",") %>%
  filter(siec %in% c("C0000X0350-0370", "O4000XBIO",
                     "G3000", "TOTAL")) %>%
  select(-freq, -unit, -nrg_bal)

long_mix <- cleaned_mix %>%
  pivot_long_year(id_cols = c("country", "siec")) %>%
  mutate(siec = recode(siec,
                       "C0000X0350-0370" = "COAL",
                       "O4000XBIO"       = "OIL",
                       "G3000"           = "GAS"))

wide_mix_share <- long_mix %>%
  pivot_wider(names_from = siec, values_from = value) %>%
  mutate(across(c(COAL, GAS, OIL, TOTAL), as.numeric),
         fossil_share = 100 * (COAL + GAS + OIL) / TOTAL) %>%
```

```
  select(country, date, COAL, GAS, OIL, fossil_share)

# -------------------------
#    ENERGY CONSUMPTION
#       PER CAPITA
#    (MWh&GWh/person)
# -------------------------
energy_cons <- raw_energy %>%
  separate(col = 1,
           into = c("freq", "unit", "siec",
                    "nrg_bal", "country"),
           sep = ",") %>%
  filter(siec == "TOTAL") %>%
  select(-freq, -unit, -nrg_bal)

long_energy_total <- energy_cons %>%
  pivot_long_year(id_cols = c("country")) %>%
  mutate(total_energy_gwh = as.numeric(na_if(value, ":"))) %>%
  select(country, date, total_energy_gwh)

# Divide by population
energy_per_capita <- long_energy_total %>%
  left_join(pop_data, by = c("country", "date")) %>%
  mutate(energy_per_capita_gwh = total_energy_gwh / population,
         energy_per_capita_mwh = energy_per_capita_gwh * 1000) %>%
```

```
  select(country, date, energy_per_capita_gwh, energy_per_capita_mwh)


# -------------------------
#       MERGE DATA
# -------------------------
merged_annual_data <- pop_data %>%
  full_join(gdp_data,         by = c("country", "date")) %>%
  full_join(wide_mix_share,  by = c("country", "date")) %>%
  full_join(energy_per_capita, by = c("country", "date")) %>%
  arrange(country, date)

# Annual CSV
write_csv(merged_annual_data, "merged_annual_data.csv")

#-----------------------------------------------------------------------------
#                          DiD Pipeline
#-----------------------------------------------------------------------------

#-----------------------------------------------------------------------------
#                          prep data
#-----------------------------------------------------------------------------

year_month_merged <- read_csv("merged_monthly_energy_dataset.csv") %>%
  mutate(year = year(date)) %>%
```

```
  left_join(
    read_csv("merged_annual_data.csv") %>%
      mutate(year = year(date)) %>%
      select(-date),
    by = c("country", "year")
  ) %>%
  mutate(
    log_Renewables_PC = log1p(Total_Renewables_PC),
    log_Renewables_Gwh = log1p(Total_Renewables_GWH),
    log_gdp_pc_pps    = log1p(gdp_pc_pps),
    log_energy_pc_mwh = log1p(energy_per_capita_mwh)
  ) %>%
  mutate(
    post_t = if_else(tname >= 202203, 1, 0),
    pre_dep_share = pre_dep_share * 100
  )

cont_did_data <- year_month_merged %>%
  select(country, date, tname, post_t, pre_dep_share,
         log_Renewables_PC, log_Renewables_Gwh, Total_Renewables_PC, Total_Renewables_GWH,
         fossil_share, log_energy_pc_mwh, log_gdp_pc_pps,
         gas_stock_mcm, coal_consumption_tht, gas_consumption_mcm, population)

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

```
#        Continuous DiD models (pre/post)
#---------------------------------------------------------------------------

cont_mod_PC <- cont_did_data %>%
  feols(Total_Renewables_PC ~ pre_dep_share * post_t | country + date,
        cluster = ~ country, .)

cont_mod_PC_2 <- cont_did_data %>%
  feols(Total_Renewables_PC ~ pre_dep_share * post_t +
          gas_stock_mcm + fossil_share + log_energy_pc_mwh + log_gdp_pc_pps + population |
          country + date,
        cluster = ~ country, .)

cont_mod_Gwh <- cont_did_data %>%
  feols(Total_Renewables_GWH ~ pre_dep_share * post_t | country + date,
        cluster = ~ country, .)

cont_mod_Gwh_2 <- cont_did_data %>%
  feols(Total_Renewables_GWH ~ pre_dep_share * post_t +
          gas_stock_mcm + fossil_share + log_energy_pc_mwh + log_gdp_pc_pps + population |
          country + date,
        cluster = ~ country, .)

```

```
# Log transformed robustness (Robustness)

#cont_mod_PC <- cont_did_data %>% feols(log_Renewables_PC ~ pre_dep_share * post_t | country + date, cluster = ~ country, .)

#cont_mod_PC_2 <- cont_did_data %>% feols(log_Renewables_PC ~ pre_dep_share * post_t + gas_stock_mcm + fossil_share + log_energy_pc_mwh + log_gdp_pc_pps + population | country + date, cluster = ~ country, .)

#cont_mod_Gwh <- cont_did_data %>% feols(log_Renewables_Gwh ~ pre_dep_share * post_t | country + date, cluster = ~ country, .)

#cont_mod_Gwh_2 <- cont_did_data %>% feols(log_Renewables_Gwh ~ pre_dep_share * post_t + gas_stock_mcm + fossil_share + log_energy_pc_mwh + log_gdp_pc_pps + population | country + date, cluster = ~ country, .)

#Additional outcomes as robustness checks
#cont_mod_gas <- cont_did_data %>%
#  feols(gas_consumption_mcm ~ pre_dep_share * post_t | country + date,
#        cluster = ~ country, .)

#cont_mod_coal <- cont_did_data %>%
#  feols(coal_consumption_tht ~ pre_dep_share * post_t | country + date,
#        cluster = ~ country, .)
```

```
#-----------------------------Tables and Figures--------------------------------

term <- "pre_dep_share:post_t"

ct1 <- summary(cont_mod_PC)$coeftable
e1  <- ct1[term,"Estimate"];
s1 <- ct1[term,"Std. Error"];
p1 <- ct1[term, grep("^Pr", colnames(ct1))]

ct2 <- summary(cont_mod_PC_2)$coeftable
e2  <- ct2[term,"Estimate"];
s2 <- ct2[term,"Std. Error"];
p2 <- ct2[term, grep("^Pr", colnames(ct2))]

ct3 <- summary(cont_mod_Gwh)$coeftable
e3  <- ct3[term,"Estimate"];
s3 <- ct3[term,"Std. Error"];
p3 <- ct3[term, grep("^Pr", colnames(ct3))]

ct4 <- summary(cont_mod_Gwh_2)$coeftable
e4  <- ct4[term,"Estimate"];
s4 <- ct4[term,"Std. Error"];
p4 <- ct4[term, grep("^Pr", colnames(ct4))]

specs <- c("TWFE PC (no controls)",
```

```
          "TWFE PC (controls)",
          "TWFE GWh (no controls)",
          "TWFE GWh (controls)")
specs_PC <- c("TWFE PC (no controls)",
          "TWFE PC (controls)")
specs_Gwh <-  c("TWFE GWh (no controls)",
             "TWFE GWh (controls)")

table_dy <- tibble(
  spec     = specs,
  term     = term,
  estimate = c(e1, e2, e3, e4),
  se       = c(s1, s2, s3, s4),
  ci_low   = estimate - 1.96 * se,
  ci_high  = estimate + 1.96 * se,
  p_value  = c(p1, p2, p3, p4)
)

table_dy_PC <- tibble(
  spec     = specs_PC,
  term     = term,
  estimate = c(e1, e2),
  se       = c(s1, s2),
  ci_low   = estimate - 1.96 * se,
  ci_high  = estimate + 1.96 * se,
```

```
  p_value  = c(p1, p2)
)

table_dy_Gwh <- tibble(
  spec     = specs_Gwh,
  term     = term,
  estimate = c(e3, e4),
  se       = c(s3, s4),
  ci_low   = estimate - 1.96 * se,
  ci_high  = estimate + 1.96 * se,
  p_value  = c(p3, p4)
)

table_dy
table_dy_PC
table_dy_Gwh

F_cont_PC <- ggplot(
  table_dy_PC,
  aes(x = estimate, y = factor(spec, levels = rev(specs_PC)))
) +
  geom_vline(xintercept = 0, linetype = "dotted") +
  geom_pointrange(aes(xmin = ci_low, xmax = ci_high)) +
  labs(
    title = "Effect of Pre-war Dependence in the Post Period",
```

```
    subtitle = "Coefficient on Pre. Dep. × post_t",
    x = "Change in renewables share (pp)",
    y = NULL,
    caption = "Post period begins Mar-2022.\n Pre dependence share = 2019–2021 mean Russian share of total gas imports.\n Points = estimates; lines = 95% CIs."
  ) +
  theme_minimal()

F_cont_Gwh <- ggplot(
  table_dy_Gwh,
  aes(x = estimate, y = factor(spec, levels = rev(specs_Gwh)))
) +
  geom_vline(xintercept = 0, linetype = "dotted") +
  geom_pointrange(aes(xmin = ci_low, xmax = ci_high)) +
  labs(
    title = "Effect of Pre-war Dependence in the Post Period",
    subtitle = "Coefficient on Pre. Dep. × post_t",
    x = "Change in renewables (GWh/month)",
    y = NULL,
    caption = "Post period begins Mar-2022.\n  Pre dependence share = 2019–2021 mean Russian share of total gas imports.\n Points = estimates; lines = 95% CIs"
  ) +
  theme_minimal()

F_cont_PC
```

```
F_cont_Gwh

#---------------------------------------------------------------------------
#              DiD dynamic (event-time) models
#---------------------------------------------------------------------------

cont_did_data <- cont_did_data %>%
  mutate(
    rel_month = (year(date) - 2022L) * 12L +
      (month(date) - 3L)
  )

#Dynamic model for renewables share (PC)
dy_mod_PC <- cont_did_data %>%
  feols(Total_Renewables_PC ~ i(rel_month, pre_dep_share, ref = -1) |
          country + date, .)

#Dynamic model for renewables level (GWh)
dy_mod_Gwh <- cont_did_data %>%
  feols(Total_Renewables_GWH ~ i(rel_month, pre_dep_share, ref = -1) |
          country + date, .)

#Predictions for dynamic model
prs_PC <- avg_predictions(dy_mod_PC, variables = c("pre_dep_share",
"rel_month"))
```

```
prs_Gwh <- avg_predictions(dy_mod_Gwh, variables = c("pre_dep_share", "rel_month"))

summary(prs_PC)
summary(prs_Gwh)
#----------------------------Tables and Figures-------------------------------

F_dy_PC <- prs_PC %>%
  mutate(months = as.numeric(as.character(rel_month)),
         pre_dep_share = as.factor(round(pre_dep_share,2))) %>%
  ggplot(aes(x = months, y = estimate, ymin = conf.low, ymax = conf.high,
             colour = pre_dep_share, fill = pre_dep_share)) +
  geom_ribbon(alpha = .25, colour = NA) +
  geom_line() +
  geom_vline(xintercept = -1, linetype = "dashed") +
  labs(
    title = "Dynamic DiD: Renewables Share (PC)",
    x = "Months relative to Mar-2022 (k)",
    y = "Predicted renewables share (pp)",
    colour = "Pre-war Dep.", fill = "Pre-war Dep."
  ) +
  theme_minimal()

F_dy_Gwh <- prs_Gwh %>%
  mutate(months = as.numeric(as.character(rel_month)),
```

```
      pre_dep_share = as.factor(round(pre_dep_share,2))) %>%
  ggplot(aes(x = months, y = estimate, ymin = conf.low, ymax = conf.high,
             colour = pre_dep_share, fill = pre_dep_share)) +
  geom_ribbon(alpha = .25, colour = NA) +
  geom_line() +
  geom_vline(xintercept = -1, linetype = "dashed") +
  labs(
    title = "Dynamic DiD: Renewables Level (Gwh)",
    x = "Months relative to Mar-2022 (k)",
    y = "Predicted renewables Level (Gwh)",
    colour = "Pre-war dep.", fill = "Pre-war dep."
    )+
  theme_minimal()

F_dy_PC
F_dy_Gwh

#---------------------------------------------------------------------------
#            Categorical exposure models
#---------------------------------------------------------------------------

cont_did_data <- cont_did_data %>%
  mutate(
    dep_cat = cut(pre_dep_share, c(-Inf, 10, 40, Inf),
                  labels = c("Low", "Medium", "High"))
```

```
)

cat_mod_PC <- cont_did_data %>%
  feols(Total_Renewables_PC ~ i(rel_month, dep_cat, ref = -1) |
          country, .)

cat_mod_Gwh <- cont_did_data %>%
  feols(Total_Renewables_GWH ~ i(rel_month, dep_cat, ref = -1) |
          country, .)

#categorical pred
cat_prs_PC <- avg_predictions(cat_mod_PC, variables = c("dep_cat", "rel_month"))
cat_prs_Gwh <- avg_predictions(cat_mod_Gwh, variables = c("dep_cat",
"rel_month"))

F_cat_PC <- cat_prs_PC %>%
  mutate(months = as.numeric(as.character(rel_month))) %>%
  ggplot(aes(x = months, y = estimate, ymin = conf.low, ymax = conf.high,
             colour = dep_cat, fill = dep_cat)) +
  geom_ribbon(alpha = .25, colour = NA) +
  geom_line() +
  geom_vline(xintercept = -1, linetype = "dashed") +
  labs(
    title = "Categorical DiD: Renewables Share (PC)",
    x = "Months relative to Mar-2022 (k)",
```

```
    y = "Predicted renewables share (%)",
    colour = "Pre-war dependence",
    fill   = "Pre-war dependence"
  ) +
  theme_minimal()

F_cat_Gwh <- cat_prs_Gwh %>%
  mutate(months = as.numeric(as.character(rel_month))) %>%
  ggplot(aes(x = months, y = estimate, ymin = conf.low, ymax = conf.high,
             colour = dep_cat, fill = dep_cat)) +
  geom_ribbon(alpha = .25, colour = NA) +
  geom_line() +
  geom_vline(xintercept = -1, linetype = "dashed") +
  labs(
    title = "Categorical DiD: Renewables Level (GWh)",
    x = "Months relative to Mar-2022 (k)",
    y = "Predicted renewables (GWh)",
    colour = "Pre-war dependence",
    fill   = "Pre-war dependence"
  ) +
  theme_minimal()

F_cat_PC
F_cat_Gwh

```

```
#---------------------------------------------------------------------------
#             Callaway & Sant'Anna (C&S) DiD estimators
#---------------------------------------------------------------------------

analysis_data_cs <- year_month_merged %>%
  mutate(idname = as.numeric(factor(country, levels = unique(country))))

analysis_data_cs <-analysis_data_cs %>%
  select(idname, country, date, treat, gname, tname, pre_dep_share,
         Total_Renewables_PC, Total_Renewables_GWH,
         log_gdp_pc_pps)

# Convert monthly to quarterly and create new treatment variables
analysis_data_cs <- analysis_data_cs %>%
  mutate(
    year          = tname %/% 100L,
    month          = tname %%  100L,
    quarter        = ((month - 1L) %/% 3L) + 1L,
    quarter_index   = as.integer(year - min(year)) * 4 + quarter)%>%
  group_by(idname) %>%
  mutate(
    trt_year    = gname %/% 100L,
    trt_month   = gname %% 100L,
    trt_quarter = ((trt_month - 1L) %/% 3L) + 1L,
```

```
    first_trt_quarter = ifelse(
      gname == 0L, 0L,
      quarter_index[tname == gname]),
  )%>%
  ungroup()%>%
  # Waves due to tiny cohorts and some naming issues
  # Mental note:
  #   1st half 2022 (Q2    2022) -> wave 1
  #   2nd half 2022 (Q3–Q4 2022) -> wave 2
  #   1st half 2023 (Q1–Q2 2023) -> wave 3
  mutate(
    pooled_wave = case_when(
      first_trt_quarter == 0L                ~ 0L,  # never treated
      first_trt_quarter %in% c(18L)          ~ 18L,  # wave 1
      first_trt_quarter %in% c(19L, 20L)     ~ 20L,  # wave 2
      first_trt_quarter %in% c(21L, 22L)     ~ 21L,  # wave 3
      TRUE                                   ~ first_trt_quarter
    ))
ref_q <- 8

wave_summary <- analysis_data_cs %>%
  group_by(pooled_wave) %>%
  summarise(
    first_trt_quarter = ifelse(unique(pooled_wave) == 0L, NA_integer_,
                               min(first_trt_quarter[first_trt_quarter > 0])),
```

```
    num_countries = n_distinct(idname),
    avg_prewar_dep = mean(pre_dep_share[year < 2022], na.rm = TRUE),
    pre_quarters = first_trt_quarter - ref_q,
    post_quarters = mean(max(quarter_index) - first_trt_quarter, na.rm = TRUE)
  ) %>%
  arrange(first_trt_quarter)

# Outcome and control to quarter level
analysis_data_cs <- analysis_data_cs %>%
  group_by(idname, country, quarter_index, gname, pooled_wave) %>%
  summarise(
    renewables      = mean(Total_Renewables_PC, na.rm = TRUE),
    renewables_Gwh  = mean(Total_Renewables_GWH, na.rm = TRUE),
    log_gdp         = mean(log_gdp_pc_pps,     na.rm = TRUE),
    .groups         = "drop"
  ) %>%
  filter(is.finite(renewables))

# Keep units with a single cohort and drop units treated at entry
analysis_data_cs <- analysis_data_cs %>%
  group_by(idname) %>% filter(n_distinct(pooled_wave) == 1L) %>% ungroup() %>%
  group_by(idname) %>%
  mutate(first_obs_q = min(quarter_index), gval = unique(pooled_wave)) %>%
  ungroup() %>%
```

```
  filter(!(gval > 0L & gval <= first_obs_q)) %>%
  select(-first_obs_q, -gval)

#---------------------------------------------------------------------------
#                    WAR SPECIFICATION (2022Q1-2024Q4)
#---------------------------------------------------------------------------

# War window (2020Q1–2024Q4)
war_data <- analysis_data_cs %>%
  filter(quarter_index >= 9L & quarter_index <= 28L)

#

# Renewables % - nevertreated
att_war_never <- att_gt(
  yname   = "renewables",
  tname   = "quarter_index",
  idname  = "idname",
  gname   = "pooled_wave",
  xformla = ~ log_gdp,
  data    = war_data,
  control_group = "nevertreated",
  anticipation  = 0,
  bstrap   = TRUE,
  clustervars = "idname"
```

```
)
summary(att_war_never)

# Renewables % - nyt  (robustness)
att_war_nyt <- att_gt(
  yname   = "renewables",
  tname   = "quarter_index",
  idname  = "idname",
  gname   = "pooled_wave",
  xformla = ~ log_gdp,
  data    = war_data,
  control_group = "notyettreated",
  anticipation  = 0,
  bstrap   = TRUE,
  clustervars = "idname"
)
summary(att_war_nyt)

# Renewables Gwh - nevertreated
att_war_never_Gwh <- att_gt(
  yname   = "renewables_Gwh",
  tname   = "quarter_index",
  idname  = "idname",
  gname   = "pooled_wave",
  xformla = ~ log_gdp,
```

```
  data    = war_data,
  control_group = "nevertreated",
  anticipation  = 0,
  bstrap   = TRUE,
  clustervars = "idname"
)
summary(att_war_never_Gwh)

# Renewables Gwh - nyt (robustness)
att_war_nyt_Gwh <- att_gt(
  yname   = "renewables_Gwh",
  tname   = "quarter_index",
  idname  = "idname",
  gname   = "pooled_wave",
  xformla = ~ log_gdp,
  data    = war_data,
  control_group = "notyettreated",
  anticipation  = 0,
  bstrap   = TRUE,
  clustervars = "idname"
)
summary(att_war_nyt_Gwh)

# Event-study curves
es_war_never <- aggte(att_war_never, type = "dynamic")
```

```
es_war_nyt   <- aggte(att_war_nyt,   type = "dynamic")
es_war_never_Gwh <- aggte(att_war_never_Gwh, type = "dynamic")
es_war_nyt_Gwh   <- aggte(att_war_nyt_Gwh,   type = "dynamic")

#--------------------------------PLOTS---------------------------------------

# Plot % nevertreated
never_war_pct_df <- data.frame(
  event_time = es_war_never$egt,
  att        = es_war_never$att.egt,
  se         = es_war_never$se.egt
) %>%
  mutate(
    ci_lower = att - qnorm(0.975) * se,
    ci_upper = att + qnorm(0.975) * se
  )

ggdid(es_war_never)+
  theme_minimal() +
  labs(
    title = "Event-Study: Treatment Effects on Renewables (%)",
    subtitle = "War - Never-treated",
    x = "Quarters relative to treatment",
    y = "ATT estimate"
  ) +
```

```
  theme(
    plot.title = element_text(size = 14, face = "bold"),
    axis.text = element_text(size = 12),
    legend.position = "bottom"
  )


# Plot % nyt
nyt_war_pct_df <- data.frame(
  event_time = es_war_nyt$egt,
  att        = es_war_nyt$att.egt,
  se         = es_war_nyt$se.egt
) %>%
  mutate(
    ci_lower = att - qnorm(0.975) * se,
    ci_upper = att + qnorm(0.975) * se
  )

ggdid(es_war_nyt)+
  theme_minimal() +
  labs(
    title = "Event-Study: Treatment Effects on Renewables (%)",
    subtitle = "War - Not-yet-treated",
    x = "Quarters relative to treatment",
    y = "ATT estimate"
```

```
  ) +
  theme(
    plot.title = element_text(size = 14, face = "bold"),
    axis.text = element_text(size = 12),
    legend.position = "bottom"
  )

# Plot Gwh nevertreated
never_war_gwh_df <- data.frame(
  event_time = es_war_never_Gwh$egt,
  att        = es_war_never_Gwh$att.egt,
  se         = es_war_never_Gwh$se.egt
) %>%
  mutate(
    ci_lower = att - qnorm(0.975) * se,
    ci_upper = att + qnorm(0.975) * se
  )

ggdid(es_war_never_Gwh)+
  theme_minimal() +
  labs(
    title = "Event-Study: Treatment Effects on Renewables (Gwh)",
    subtitle = "War - Never-treated",
    x = "Quarters relative to treatment",
    y = "ATT estimate"
```

```
  ) +
  theme(
    plot.title = element_text(size = 14, face = "bold"),
    axis.text = element_text(size = 12),
    legend.position = "bottom"
  )

# Plot Gwh nyt
nyt_war_gwh_df <- data.frame(
  event_time = es_war_nyt_Gwh$egt,
  att        = es_war_nyt_Gwh$att.egt,
  se         = es_war_nyt_Gwh$se.egt
) %>%
  mutate(
    ci_lower = att - qnorm(0.975) * se,
    ci_upper = att + qnorm(0.975) * se
  )

ggdid(es_war_nyt_Gwh)+
  theme_minimal() +
  labs(
    title = "Event-Study: Treatment Effects on Renewables (Gwh)",
    subtitle = "War - Not-yet-treated",
    x = "Quarters relative to treatment",
    y = "ATT estimate"
```

```
  ) +
  theme(
    plot.title = element_text(size = 14, face = "bold"),
    axis.text = element_text(size = 12),
    legend.position = "bottom"
  )

ov_never <-  aggte(att_war_never, type = "simple")
ov_nyt   <-  aggte(att_war_nyt,   type = "simple")

t6_cs <- data.frame(
  Model   = c("C&S ATT (never-treated)", "C&S ATT (not-yet-treated)"),
  Outcome = c("Renewables (%)",          "Renewables (%)"),
  Est     = c(ov_never$overall.att,      ov_nyt$overall.att),
  SE      = c(ov_never$overall.se,       ov_nyt$overall.se)
)
t6_cs$CI_low  <- t6_cs$Est - 1.96 * t6_cs$SE
t6_cs$CI_high <- t6_cs$Est + 1.96 * t6_cs$SE

print(t6_cs)
```

```
ov_never_Gwh <-  aggte(att_war_never_Gwh, type = "simple")
ov_nyt_Gwh   <-  aggte(att_war_nyt_Gwh,   type = "simple")

t6_cs_gwh <- data.frame(
  Model = c("C&S ATT (never-treated) [GWh]", "C&S ATT (not-yet-treated) [GWh]"),
  Est   = c(ov_never_Gwh$overall.att,        ov_nyt_Gwh$overall.att),
  SE    = c(ov_never_Gwh$overall.se,         ov_nyt_Gwh$overall.se)
)
t6_cs_gwh$CI_low  <- t6_cs_gwh$Est - 1.96 * t6_cs_gwh$SE
t6_cs_gwh$CI_high <- t6_cs_gwh$Est + 1.96 * t6_cs_gwh$SE
print(t6_cs_gwh)

get_row <- function(model, spec, outcome) {
  ct <- summary(model)$coeftable
  est <- ct[term, "Estimate"]
  se <- ct[term, "Std. Error"]
  p <- ct[term, grep("^Pr", colnames(ct))]
  tibble(
    spec = spec,
    outcome = outcome,
    term = term,
    estimate = est,
    se = se,
    ci_low = est - 1.96 * se,
```

```
    ci_high = est + 1.96 * se,
    p_value = as.numeric(p)
  )
}


T6a <- bind_rows(
  get_row(cont_mod_PC, "TWFE PC (no controls)", "Renewables (%)"),
  get_row(cont_mod_PC_2, "TWFE PC (controls)", "Renewables (%)"),
  get_row(cont_mod_Gwh, "TWFE GWh (no controls)", "Renewables (GWh)"),
  get_row(cont_mod_Gwh_2, "TWFE GWh (controls)", "Renewables (GWh)")
) %>%
  mutate(across(c(estimate, se, ci_low, ci_high), ~round(.x, 3)))

print(T6a)


# Wave att_gt
# NEVERTREATED
w1_dat_never_pct <- war_data[war_data$pooled_wave %in% c(0L, 18L), ]
w1_att_never_pct <-  att_gt(yname = "renewables",
                   tname = "quarter_index",
                   idname = "idname",
                   gname = "pooled_wave",
                   xformla = ~ log_gdp,
```

```
                      data = w1_dat_never_pct,
                      control_group = "nevertreated",
                      anticipation = 0,
                      bstrap = TRUE,
                      clustervars = "idname")
w1_es_never_pct  <-  aggte(w1_att_never_pct, type = "dynamic")
w1_df_never_pct  <- data.frame(e = w1_es_never_pct$egt, att = w1_es_never_pct$att.egt, se = w1_es_never_pct$se.egt, Wave = "W1")

w2_dat_never_pct <- war_data[war_data$pooled_wave %in% c(0L, 20L), ]
w2_att_never_pct <-  att_gt(yname = "renewables",
                      tname = "quarter_index",
                      idname = "idname",
                      gname = "pooled_wave",
                      xformla = ~ log_gdp,
                      data = w2_dat_never_pct,
                      control_group = "nevertreated",
                      anticipation = 0, bstrap = TRUE,
                      clustervars = "idname")
w2_es_never_pct  <-  aggte(w2_att_never_pct, type = "dynamic")
w2_df_never_pct  <- data.frame(e = w2_es_never_pct$egt, att = w2_es_never_pct$att.egt, se = w2_es_never_pct$se.egt, Wave = "W2")

w3_dat_never_pct <- war_data[war_data$pooled_wave %in% c(0L, 21L), ]
w3_att_never_pct <-  att_gt(yname = "renewables",
```

```
                        tname = "quarter_index",
                        idname = "idname",
                        gname = "pooled_wave",
                        xformla = ~ log_gdp,
                        data = w3_dat_never_pct,
                        control_group = "nevertreated",
                        anticipation = 0,
                        bstrap = TRUE,
                        clustervars = "idname")
w3_es_never_pct  <-  aggte(w3_att_never_pct, type = "dynamic")
w3_df_never_pct  <- data.frame(e = w3_es_never_pct$egt, att = w3_es_never_pct$att.egt, se = w3_es_never_pct$se.egt, Wave = "W3")

# Combine / CI
w_never_pct <- rbind(w1_df_never_pct, w2_df_never_pct, w3_df_never_pct)
w_never_pct$lo <- w_never_pct$att - 1.96 * w_never_pct$se
w_never_pct$hi <- w_never_pct$att + 1.96 * w_never_pct$se

# NOT-YET-TREATED
w1_dat_nyt_pct <- war_data[war_data$pooled_wave %in% c(0L, 18L), ]
w1_att_nyt_pct <-  att_gt(yname = "renewables",
                       tname = "quarter_index",
                       idname = "idname",
                       gname = "pooled_wave",
                       xformla = ~ log_gdp,
```

```
                      data = w1_dat_nyt_pct,
                      control_group = "notyettreated",
                      anticipation = 0, bstrap = TRUE,
                      clustervars = "idname")
w1_es_nyt_pct  <-  aggte(w1_att_nyt_pct, type = "dynamic")
w1_df_nyt_pct  <- data.frame(e = w1_es_nyt_pct$egt, att = w1_es_nyt_pct$att.egt, se = w1_es_nyt_pct$se.egt, Wave = "W1")

w2_dat_nyt_pct <- war_data[war_data$pooled_wave %in% c(0L, 20L), ]
w2_att_nyt_pct <-  att_gt(yname = "renewables",
                      tname = "quarter_index",
                      idname = "idname",
                      gname = "pooled_wave",
                      xformla = ~ log_gdp,
                      data = w2_dat_nyt_pct,
                      control_group = "notyettreated",
                      anticipation = 0,
                      bstrap = TRUE,
                      clustervars = "idname")
w2_es_nyt_pct  <-  aggte(w2_att_nyt_pct, type = "dynamic")
w2_df_nyt_pct  <- data.frame(e = w2_es_nyt_pct$egt, att = w2_es_nyt_pct$att.egt, se = w2_es_nyt_pct$se.egt, Wave = "W2")

w3_dat_nyt_pct <- war_data[war_data$pooled_wave %in% c(0L, 21L), ]
w3_att_nyt_pct <-  att_gt(yname = "renewables",
```

```
                     tname = "quarter_index",
                     idname = "idname",
                     gname = "pooled_wave",
                     xformla = ~ log_gdp,
                     data = w3_dat_nyt_pct,
                     control_group = "notyettreated",
                     anticipation = 0, bstrap = TRUE,
                     clustervars = "idname")
w3_es_nyt_pct  <-  aggte(w3_att_nyt_pct, type = "dynamic")
w3_df_nyt_pct  <- data.frame(e = w3_es_nyt_pct$egt, att = w3_es_nyt_pct$att.egt, se = w3_es_nyt_pct$se.egt, Wave = "W3")


w_nyt_pct <- rbind(w1_df_nyt_pct, w2_df_nyt_pct, w3_df_nyt_pct)
w_nyt_pct$lo <- w_nyt_pct$att - 1.96 * w_nyt_pct$se
w_nyt_pct$hi <- w_nyt_pct$att + 1.96 * w_nyt_pct$se

# NEVERTREATED GWH
g1_dat_never_gwh <- war_data[war_data$pooled_wave %in% c(0L, 18L), ]
g1_att_never_gwh <-  att_gt(yname = "renewables_Gwh",
                      tname = "quarter_index",
                      idname = "idname",
                      gname = "pooled_wave",
                      xformla = ~ log_gdp,
                      data = g1_dat_never_gwh,
```

```
                        control_group = "nevertreated",
                        anticipation = 0,
                        bstrap = TRUE,
                        clustervars = "idname")
g1_es_never_gwh  <-  aggte(g1_att_never_gwh, type = "dynamic")
g1_df_never_gwh  <- data.frame(e = g1_es_never_gwh$egt, att = 
    g1_es_never_gwh$att.egt, se = g1_es_never_gwh$se.egt, Wave = "W1")

g2_dat_never_gwh <- war_data[war_data$pooled_wave %in% c(0L, 20L), ]
g2_att_never_gwh <-  att_gt(yname = "renewables_Gwh",
                        tname = "quarter_index",
                        idname = "idname",
                        gname = "pooled_wave",
                        xformla = ~ log_gdp,
                        data = g2_dat_never_gwh,
                        control_group = "nevertreated",
                        anticipation = 0,
                        bstrap = TRUE,
                        clustervars = "idname")
g2_es_never_gwh  <-  aggte(g2_att_never_gwh, type = "dynamic")
g2_df_never_gwh  <- data.frame(e = g2_es_never_gwh$egt, att = 
    g2_es_never_gwh$att.egt, se = g2_es_never_gwh$se.egt, Wave = "W2")

g3_dat_never_gwh <- war_data[war_data$pooled_wave %in% c(0L, 21L), ]
g3_att_never_gwh <-  att_gt(yname = "renewables_Gwh",
```

```
                        tname = "quarter_index",
                        idname = "idname",
                        gname = "pooled_wave",
                        xformla = ~ log_gdp,
                        data = g3_dat_never_gwh,
                        control_group = "nevertreated",
                        anticipation = 0,
                        bstrap = TRUE,
                        clustervars = "idname")
g3_es_never_gwh  <-  aggte(g3_att_never_gwh, type = "dynamic")
g3_df_never_gwh  <- data.frame(e = g3_es_never_gwh$egt, att = g3_es_never_gwh$att.egt, se = g3_es_never_gwh$se.egt, Wave = "W3")


w_never_gwh <- rbind(g1_df_never_gwh, g2_df_never_gwh, g3_df_never_gwh)
w_never_gwh$lo <- w_never_gwh$att - 1.96 * w_never_gwh$se
w_never_gwh$hi <- w_never_gwh$att + 1.96 * w_never_gwh$se

# NOT-YET-TREATED GWH
g1_dat_nyt_gwh <- war_data[war_data$pooled_wave %in% c(0L, 18L), ]
g1_att_nyt_gwh <-  att_gt(yname = "renewables_Gwh",
                       tname = "quarter_index",
                       idname = "idname",
                       gname = "pooled_wave",
                       xformla = ~ log_gdp,
```

```
                      data = g1_dat_nyt_gwh,
                      control_group = "notyettreated",
                      anticipation = 0,
                      bstrap = TRUE,
                      clustervars = "idname")
g1_es_nyt_gwh  <-  aggte(g1_att_nyt_gwh, type = "dynamic")
g1_df_nyt_gwh  <- data.frame(e = g1_es_nyt_gwh$egt, att = g1_es_nyt_gwh$att.egt,
se = g1_es_nyt_gwh$se.egt, Wave = "W1")

g2_dat_nyt_gwh <- war_data[war_data$pooled_wave %in% c(0L, 20L), ]
g2_att_nyt_gwh <-  att_gt(yname = "renewables_Gwh",
                      tname = "quarter_index",
                      idname = "idname",
                      gname = "pooled_wave",
                      xformla = ~ log_gdp,
                      data = g2_dat_nyt_gwh,
                      control_group = "notyettreated",
                      anticipation = 0,
                      bstrap = TRUE,
                      clustervars = "idname")
g2_es_nyt_gwh  <-  aggte(g2_att_nyt_gwh, type = "dynamic")
g2_df_nyt_gwh  <- data.frame(e = g2_es_nyt_gwh$egt, att = g2_es_nyt_gwh$att.egt,
se = g2_es_nyt_gwh$se.egt, Wave = "W2")
```

```
g3_dat_nyt_gwh <- war_data[war_data$pooled_wave %in% c(0L, 21L), ]
g3_att_nyt_gwh <-  att_gt(yname = "renewables_Gwh",
                      tname = "quarter_index",
                      idname = "idname",
                      gname = "pooled_wave",
                      xformla = ~ log_gdp,
                      data = g3_dat_nyt_gwh,
                      ontrol_group = "notyettreated",
                      anticipation = 0,
                      bstrap = TRUE,
                      clustervars = "idname")
g3_es_nyt_gwh  <-  aggte(g3_att_nyt_gwh, type = "dynamic")
g3_df_nyt_gwh  <- data.frame(e = g3_es_nyt_gwh$egt, att = g3_es_nyt_gwh$att.egt,
          se = g3_es_nyt_gwh$se.egt, Wave = "W3")


w_nyt_gwh <- rbind(g1_df_nyt_gwh, g2_df_nyt_gwh, g3_df_nyt_gwh)
w_nyt_gwh$lo <- w_nyt_gwh$att - 1.96 * w_nyt_gwh$se
w_nyt_gwh$hi <- w_nyt_gwh$att + 1.96 * w_nyt_gwh$se

#plot

p_w_never_pct <- ggplot(w_never_pct, aes(x = e, y = att, color = Wave)) +
  geom_hline(yintercept = 0) +
  geom_vline(xintercept = 0, linetype = "dashed") +
```

```
  geom_errorbar(aes(ymin = lo, ymax = hi), width = 0) +
  geom_line() + geom_point() +
  labs(x = "Quarters relative to first treatment", y = "ATT on renewables (%)",
       title = "Event-Time by Wave — % (Never-treated)") +
  theme_minimal()

p_w_never_pct

p_w_nyt_pct <- ggplot(w_nyt_pct, aes(x = e, y = att, color = Wave)) +
  geom_hline(yintercept = 0) +
  geom_vline(xintercept = 0, linetype = "dashed") +
  geom_errorbar(aes(ymin = lo, ymax = hi), width = 0) +
  geom_line() + geom_point() +
  labs(x = "Quarters relative to first treatment", y = "ATT on renewables (%)",
       title = "Event-Time by Wave — % (Not-yet-treated)") +
  theme_minimal()

p_w_nyt_pct

p_w_never_gwh <- ggplot(w_never_gwh, aes(x = e, y = att, color = Wave)) +
  geom_hline(yintercept = 0) +
  geom_vline(xintercept = 0, linetype = "dashed") +
  geom_errorbar(aes(ymin = lo, ymax = hi), width = 0) +
  geom_line() + geom_point() +
  labs(x = "Quarters relative to first treatment", y = "ATT on renewables (GWh)",
```

```
     title = "Event-Time by Wave — GWh (Never-treated)") +
  theme_minimal()

p_w_never_gwh

p_w_nyt_gwh <- ggplot(w_nyt_gwh, aes(x = e, y = att, color = Wave)) +
  geom_hline(yintercept = 0) +
  geom_vline(xintercept = 0, linetype = "dashed") +
  geom_errorbar(aes(ymin = lo, ymax = hi), width = 0) +
  geom_line() + geom_point() +
  labs(x = "Quarters relative to first treatment", y = "ATT on renewables (GWh)",
     title = "Event-Time by Wave — GWh (Not-yet-treated)") +
  theme_minimal()

p_w_nyt_gwh


t_w1_never_pct <- aggte(w1_att_never_pct, type = "simple")
t_w2_never_pct <- aggte(w2_att_never_pct, type = "simple")
t_w3_never_pct <- aggte(w3_att_never_pct, type = "simple")


t_w1_nyt_pct <- aggte(w1_att_nyt_pct, type = "simple")
t_w2_nyt_pct <- aggte(w2_att_nyt_pct, type = "simple")
t_w3_nyt_pct <- aggte(w3_att_nyt_pct, type = "simple")
```

```


t7_pct <- data.frame(
  Wave       = c("W1","W2","W3"),
  ATT_never  = c(t_w1_never_pct$overall.att, t_w2_never_pct$overall.att, t_w3_never_pct$overall.att),
  SE_never   = c(t_w1_never_pct$overall.se,  t_w2_never_pct$overall.se,  t_w3_never_pct$overall.se),
  ATT_nyt    = c(t_w1_nyt_pct$overall.att,   t_w2_nyt_pct$overall.att,   t_w3_nyt_pct$overall.att),
  SE_nyt     = c(t_w1_nyt_pct$overall.se,    t_w2_nyt_pct$overall.se,    t_w3_nyt_pct$overall.se)
)

t7_pct


t_w1_never_gwh <- aggte(g1_att_never_gwh, type = "simple")
t_w2_never_gwh <- aggte(g2_att_never_gwh, type = "simple")
t_w3_never_gwh <- aggte(g3_att_never_gwh, type = "simple")


t_w1_nyt_gwh <- aggte(g1_att_nyt_gwh, type = "simple")
t_w2_nyt_gwh <- aggte(g2_att_nyt_gwh, type = "simple")
t_w3_nyt_gwh <- aggte(g3_att_nyt_gwh, type = "simple")
```

```
t7_gwh <- data.frame(
  Wave       = c("W1","W2","W3"),
  ATT_never  = c(t_w1_never_gwh$overall.att, t_w2_never_gwh$overall.att, t_w3_never_gwh$overall.att),
  SE_never   = c(t_w1_never_gwh$overall.se,  t_w2_never_gwh$overall.se,  t_w3_never_gwh$overall.se),
  ATT_nyt    = c(t_w1_nyt_gwh$overall.att,   t_w2_nyt_gwh$overall.att,   t_w3_nyt_gwh$overall.att),
  SE_nyt     = c(t_w1_nyt_gwh$overall.se,    t_w2_nyt_gwh$overall.se,    t_w3_nyt_gwh$overall.se)
)

t7_gwh


# ---------------------- GREEN DEAL PLACEBO (2018Q1–2021Q4) --------------

# Same treated set, forced treat date 2020Q1 (20201)
gd_data <- analysis_data_cs %>%
  filter(quarter_index >= 1L & quarter_index <= 16L) %>%
  mutate(placebo_wave = ifelse(pooled_wave == 0L, 0L, 9L)) %>%
  group_by(idname) %>%
  mutate(first_obs_q = min(quarter_index), gval = unique(placebo_wave)) %>%
  ungroup() %>%
```

```
  filter(!(gval > 0L & gval <= first_obs_q)) %>%
  select(-first_obs_q, -gval)

# % nevertreated
att_gd_never <- att_gt(
  yname   = "renewables",
  tname   = "quarter_index",
  idname  = "idname",
  gname   = "placebo_wave",
  xformla = ~ log_gdp,
  data    = gd_data,
  control_group = "nevertreated",
  anticipation  = 0,
  bstrap   = TRUE,
  clustervars = "idname"
)
summary(att_gd_never)

# % nyt
att_gd_nyt <- att_gt(
  yname   = "renewables",
  tname   = "quarter_index",
  idname  = "idname",
  gname   = "placebo_wave",
  xformla = ~ log_gdp,
```

```
  data     = gd_data,
  control_group = "notyettreated",
  anticipation  = 0,
  bstrap    = TRUE,
  clustervars = "idname"
)
summary(att_gd_nyt)

# Gwh nevertreated
att_gd_never_Gwh <- att_gt(
  yname    = "renewables_Gwh",
  tname    = "quarter_index",
  idname   = "idname",
  gname    = "placebo_wave",
  xformla = ~ log_gdp,
  data     = gd_data,
  control_group = "nevertreated",
  anticipation  = 0,
  bstrap    = TRUE,
  clustervars = "idname"
)
summary(att_gd_never_Gwh)

# Gwh nyt
att_gd_nyt_Gwh <- att_gt(
```

```
  yname   = "renewables_Gwh",
  tname   = "quarter_index",
  idname  = "idname",
  gname   = "placebo_wave",
  xformla = ~ log_gdp,
  data    = gd_data,
  control_group = "notyettreated",
  anticipation  = 0,
  bstrap   = TRUE,
  clustervars = "idname"
)
summary(att_gd_never_Gwh)

es_gd_never <- aggte(att_gd_never, type = "dynamic")
es_gd_nyt   <- aggte(att_gd_nyt,   type = "dynamic")
es_gd_never_Gwh <- aggte(att_gd_never_Gwh, type = "dynamic")
es_gd_nyt_Gwh   <- aggte(att_gd_nyt_Gwh,   type = "dynamic")

ov_gd_never      <- aggte(att_gd_never,      type = "simple")
ov_gd_nyt        <- aggte(att_gd_nyt,        type = "simple")
ov_gd_never_gwh  <- aggte(att_gd_never_Gwh,  type = "simple")
ov_gd_nyt_gwh    <- aggte(att_gd_nyt_Gwh,    type = "simple")

T8 <- tibble(
  control_group = c("nevertreated", "notyettreated", "nevertreated", "notyettreated"),
```

```
  outcome      = c("Renewables (%)", "Renewables (%)", "Renewables (GWh)",
    "Renewables (GWh)"),
  controls     = "+ log_gdp",
  est          = c(ov_gd_never$overall.att, ov_gd_nyt$overall.att,
                   ov_gd_never_gwh$overall.att, ov_gd_nyt_gwh$overall.att),
  se           = c(ov_gd_never$overall.se,  ov_gd_nyt$overall.se,
                   ov_gd_never_gwh$overall.se, ov_gd_nyt_gwh$overall.se)
) %>%
  mutate(
    ci_low  = est - 1.96 * se,
    ci_high = est + 1.96 * se
  ) %>%
  mutate(across(c(est, se, ci_low, ci_high), ~round(.x, 3)))
print(T8)
#--------------------------------PLOTS----------------------------------------
# Plot % nevertreated
never_gd_pct_df <- data.frame(
  event_time = es_gd_never$egt,
  att        = es_gd_never$att.egt,
  se         = es_gd_never$se.egt
) %>%
  mutate(
```

```
    ci_lower = att - qnorm(0.975) * se,
    ci_upper = att + qnorm(0.975) * se
  )

ggdid(es_gd_never)+
  theme_minimal() +
  labs(
    title = "Event-Study: Treatment Effects on Renewables (%)",
    subtitle = "Green Deal - Never-treated",
    x = "Quarters relative to treatment",
    y = "ATT estimate"
  ) +
  theme(
    plot.title = element_text(size = 14, face = "bold"),
    axis.text = element_text(size = 12),
    legend.position = "bottom"
  )

# Plot % nyt
nyt_gd_pct_df <- data.frame(
  event_time = es_gd_nyt$egt,
  att        = es_gd_nyt$att.egt,
  se         = es_gd_nyt$se.egt
) %>%
  mutate(
```

```
    ci_lower = att - qnorm(0.975) * se,
    ci_upper = att + qnorm(0.975) * se
  )

ggdid(es_gd_nyt)+
  theme_minimal() +
  labs(
    title = "Event-Study: Treatment Effects on Renewables (%)",
    subtitle = "Green Deal - Not-yet-treated",
    x = "Quarters relative to treatment",
    y = "ATT estimate"
  ) +
  theme(
    plot.title = element_text(size = 14, face = "bold"),
    axis.text = element_text(size = 12),
    legend.position = "bottom"
  )

# Plot Gwh nevertreated
never_gd_gwh_df <- data.frame(
  event_time = es_gd_never_Gwh$egt,
  att        = es_gd_never_Gwh$att.egt,
  se         = es_gd_never_Gwh$se.egt
) %>%
  mutate(
```

```
    ci_lower = att - qnorm(0.975) * se,
    ci_upper = att + qnorm(0.975) * se
  )

ggdid(es_gd_never_Gwh)+
  theme_minimal() +
  labs(
    title = "Event-Study: Treatment Effects on Renewables (Gwh)",
    subtitle = "Green Deal - Never-treated",
    x = "Quarters relative to treatment",
    y = "ATT estimate"
  ) +
  theme(
    plot.title = element_text(size = 14, face = "bold"),
    axis.text = element_text(size = 12),
    legend.position = "bottom"
  )

# Plot Gwh nyt
nyt_gd_gwh_df <- data.frame(
  event_time = es_gd_nyt_Gwh$egt,
  att        = es_gd_nyt_Gwh$att.egt,
  se         = es_gd_nyt_Gwh$se.egt
) %>%
  mutate(
```

```
    ci_lower = att - qnorm(0.975) * se,
    ci_upper = att + qnorm(0.975) * se
  )

ggdid(es_gd_nyt_Gwh)+
  theme_minimal() +
  labs(
    title = "Event-Study: Treatment Effects on Renewables (Gwh)",
    subtitle = "Green Deal - Not-yet-treated",
    x = "Quarters relative to treatment",
    y = "ATT estimate"
  ) +
  theme(
    plot.title = element_text(size = 14, face = "bold"),
    axis.text = element_text(size = 12),
    legend.position = "bottom"
  )


#---------------------------------------------------------------------------
#           Overall Data  Descriptive plots and tables
#---------------------------------------------------------------------------

fig1_data <- year_month_merged %>%
  distinct(country, pre_dep_share)
```

```
ggplot(fig1_data, aes(x = reorder(country, pre_dep_share), y = pre_dep_share ,colour = country, fill = country)) +
  geom_col() +
  coord_flip() +
  labs(x = NULL, y = "Avg. Russian dependence, 2019–21 (pp)")+
  theme(legend.position = "none")

bins <- year_month_merged %>%
  distinct(country, pre_dep_share) %>%
  mutate(bin = case_when(
    pre_dep_share <= 10 ~ "Low (≤10pp)",
    pre_dep_share > 40  ~ "High (>40pp)",
    TRUE ~ NA_character_
  ))

traj <- year_month_merged %>%
  left_join(bins, by = "country") %>%
  filter(!is.na(bin)) %>%
  group_by(date, bin) %>%
  summarise(mean_pc = mean(Total_Renewables_PC, na.rm = TRUE), .groups = "drop")

ggplot(traj, aes(x = date, y = mean_pc, color = bin)) +
  geom_line() +
```

```
  geom_vline(xintercept = as.Date("2022-03-01")) +
  labs(x = NULL, y = "Renewables (% of consumption)",
       colour = "Dependence level", fill = "Dependence level")


vars <- c("Total_Renewables_PC","Total_Renewables_GWH","pre_dep_share",
          "log_gdp_pc_pps","log_energy_pc_mwh",
          "gas_stock_mcm",
          "population")

make_stats <- function(df, vars) {
  df %>%
    summarise(across(all_of(vars),
                     list(mean = ~round(mean(.x, na.rm = TRUE), 2),
                          sd   = ~round(sd(.x,   na.rm = TRUE), 2),
                          min  = ~round(min(.x,  na.rm = TRUE), 2),
                          max  = ~round(max(.x,  na.rm = TRUE), 2),
                          N    = ~sum(!is.na(.x))),
                     .names = "{.col}_{.fn}")) %>%
    pivot_longer(everything(),
                 names_to = c("variable","stat"),
                 names_pattern = "^(.*)_(mean|sd|min|max|N)$",
                 values_to = "value") %>%
    pivot_wider(names_from = stat, values_from = value)
}
```

```

# Overall
t4_overall <- make_stats(year_month_merged, vars)
write_csv(t4_overall, "tables/T4_overall.csv")

# Pre
t4_pre <- make_stats(filter(year_month_merged, tname < 202203), vars)
write_csv(t4_pre, "tables/T4_pre.csv")

# Post
t4_post <- make_stats(filter(year_month_merged, tname >= 202203), vars)
write_csv(t4_post, "tables/T4_post.csv")


t5 <- analysis_data_cs %>%
  distinct(country, pooled_wave) %>%
  left_join(year_month_merged %>% distinct(country, pre_dep_share), by =
"country") %>%
  mutate(wave = recode(pooled_wave,
                       `18` = "W1=18",
                       `20` = "W2=20",
                       `21` = "W3=21",
                       `0`  = "Never",
                       .default = as.character(pooled_wave))) %>%
  group_by(pooled_wave, wave) %>%
```

```
summarise(
  n_countries    = n(),
  mean_pre_dep   = mean(pre_dep_share, na.rm = TRUE),
  median_pre_dep = median(pre_dep_share, na.rm = TRUE),
  iqr_pre_dep    = IQR(pre_dep_share, na.rm = TRUE),
  countries      = paste(sort(country), collapse = ", "),
  .groups = "drop"
) %>%
 arrange(pooled_wave)
```