The following paper was researched and written as part of LSE GROUPS 2025.

LSE GROUPS takes place during the final fortnight of the LSE Spring Term. Undergraduate students are placed in small groups; these are cross-year, interdisciplinary, and group members do not know one another in advance. Each group must then devise its own research question and carry out every stage of a small-scale research project, in less than two weeks.

LSE GROUPS is part of the LSE commitment to students learning through enquiry and developing the skills needed for knowledge creation.

The overall theme of LSE GROUPS 2025 was *Visions for the Future*

This paper was submitted on the final Thursday afternoon of the project. Students then presented their work at a conference, on the closing Friday.

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London School of Economics and Political Science

Closer to Washington, Further from Paris: Does Alignment with the US affect Countries' Green Investment post US-Praxit?

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Abstract

In June 2017, Trump announced the US withdrawal from the Paris Agreement, sparking heated debate on the future of climate policy. Previous literature has examined the US withdrawal's impact on emission targets (Larch & Wanner, 2024), domestic green financial markets (Pham et al., 2023), and regional green equities (Alessi et al., 2024). This paper takes a broader view, analyzing how US policy shifts and countries' political-economic alignment with the US have influenced global public renewable energy investment (green investment). We employ a two-way random effects continuous difference-in-differences model to isolate the effects of US alignment on green investment patterns. Using panel data from 2016-2021, we find a statistically significant effect of a 1% increase in trade alignment with the US is associated with a 0.701% decrease in public green investment. We find no significant effects for climate aid, military aid, or institutional alignment, and heterogeneity tests confirm no significant differences between development groups (all p>0.50). These results suggest that trade-based alignment with the US creates universal constraints on green investment regardless of development status, highlighting the vulnerability of global climate finance to major economies' policy shifts.

Keywords: Paris Agreement withdrawal, Green investment, Climate policy, US alignment, Renewable energy investment, Difference-in-differences.

1 Introduction

Over the past decade, the US has signed the Paris Agreement and subsequently withdrawn from it twice (Noor, 2025). As a global hegemon (Norloff, 2010), US environmental commitment critically shapes local and global mitigation efforts, though impacts vary across countries. The existing academic literature on the US withdrawal from the Paris Agreement primarily focuses on effects on carbon emissions, or green investment changes of a limited number of countries (Larch & Wanner, 2024; Zhang et al., 2017). We aim to bridge this gap in examining how countries' alignment with the US influences their green investment decisions in the context of US's climate policy swings, to gauge the resilience of the commitment to global climate change mitigation. We analysed how the US withdrawal affected green investment by employing a two-way random effects continuous difference-in-differences model. Additionally, we investigated whether these effects differ across countries' development groups. Our findings show that only trade dependency exhibits a statistically significant effect, while heterogeneity tests confirm no significant differences across development groups.

2 Literature Review

The United States (US) presents a unique paradox in global climate governance. Despite 73% voter support for climate action (Leiserowitz et al., 2024), US participation in the 2015 Paris Agreement has become a clear partisan division—Obama joined, Trump withdrew (2017), Biden rejoined (2021), and Trump withdrew again (2025) (Lazarou & Leclerc, 2025; Haskett, 2025). This volatility influences both the US's domestic market and global politics; with the stock market fluctuations particularly in green sectors, spiking with each policy shift (Pham et al., 2023). EU investors increased holdings of carbon-intensive assets following Trump's withdrawal announcement (Alessi et al., 2024). More critically, without US participation, 31% of global emission reductions is estimated to be lost, with the US producing 9.5% more carbon emissions domestically (Larch & Wanner, 2024). Yet despite these documented market reactions, no research has systematically examined how countries' multifaceted alignment with the US influences their green investment decisions in this volatile context. Existing literature establishes that alignment with another country shapes investment flows through multiple channels, each relevant to understanding green investment patterns:

2.1 Diplomatic affinity

Diplomatic affinity significantly increases bilateral FDI flows, commonly measured through UN General Assembly voting patterns (Lin et al., 2024; Khan, 2020; Dreher & Jensen, 2013). According to Lin et al. (2024), a one standard deviation increase in diplomatic affinity, corresponds to a 0.320 unit rise in FDI flows, accounting to 12.4% of the sample mean. This matters particularly for green investment, as developing economies rely heavily on green FDI to meet climate goals (Jaumotte et al., 2024; Botwright & Stephenson, 2023). The Green Climate Fund exemplifies this dynamic—following the 2017 US withdrawal, $2 billion of America's $3 billion pledge remained unfulfilled (Climate Funds Update, 2017), intensifying competition for limited climate finance among aligned nations.

2.2 Trade dependency

Trade relationships transmit policy shocks through competition and coercion (Simmons et al., 2007). Geopolitically aligned nations maintain 2.5% higher quarter-on-quarter trade volumes over six-year periods (Qui et al., 2024), creating vulnerabilities when major partners shift policies. Withdrawal from the Paris Agreement changes US demand for environmental goods and services, which can reduce trade volumes and depress prices, disincentivising green investment through diminished returns among trade-dependent allies (Larch & Wanner, 2022; Arezki & Matsumoto, 2017; Nong & Siriwardana, 2018).

2.3 Military Alignment

Though understudied in climate contexts, military relationships create powerful compliance incentives. The Arms for Influence model demonstrates that US military aid to Georgia tripled bilateral cooperation (Sullivan et al., 2011), illustrating how aid creates dependency dynamics (Keohane and Nye, 1973; Bueno de Mesquita and Smith, 2007). Critically, development aid correlates with increased military expenditures in recipient countries (Langlotz & Potrafke, 2019), while higher military spending negatively correlates with green investments across G20 countries (Demirtaş et al., 2023).

2.4 Climate Aid

Climate aid allocation follows donors' economic and security relationships rather than environmental needs (Lewis, 2003), making recipients vulnerable to donors' policy swings. When the US withdraws from climate commitments, environmental aid funding decreases (Rose & Estes, 2021), directly impacting green investment capacity of the recipient country. Research confirms climate aid significantly promotes renewable energy investment, both directly through resources and indirectly through technology transfer (Zeng et al., 2022; Wu et al., 2021; Villanthenkodath et al., 2021).

2.5 Current Study

While these studies establish how alignment influences investment generally, they share a critical limitation: none examine how alignment specifically mediates the relationship between US climate policy volatility and global green investment patterns. Existing research either analyzes stable donor-recipient relationships without accounting for policy reversals; examines bilateral investment flows without isolating green investment; focuses on other major economies with more consistent climate policies. This gap is particularly glaring given the US's unique position as both the world's largest economy and most volatile climate policy actor among developed nations (Heath, 2024). As Zhang et al. (2017) note, the US plays a pivotal role in setting global climate examples, yet we lack systematic understanding of how its policy swings affect aligned countries' green investment decisions.

This study addresses this gap by asking:

RQ: How does multidimensional alignment with the United States—through diplomatic, trade, military, and climate aid channels—influence countries' green investment responses to the US Paris Agreement withdrawal announcement?

3 Method

We examine how the US withdrawal from the Paris Agreement on June 1, 2017, affected green investment in countries with varying levels of pre-existing alignment with the United States. Although there were prior discussions on whether the US should leave the Paris Agreement, it was uncertain that Trump was going to pull out due to support for US involvement from multiple groups, including some of Trump's advisors, Republican congressmen, and large corporations such as Exxon Mobil (Milman, 2017). Since the withdrawal was driven by domestic US political decisions rather than contemporaneous shifts in other countries' green investment patterns, and there was no precise pre-announcement scheduling that foreign actors could anticipate, we treat the timing as exogenous.

H1: The US withdrawal from the Paris Agreement significantly affected green investment from countries with higher pre-2017 alignment with the United States, with the magnitude of effect varying by the type of alignment.

We hypothesize that US withdrawal impacts green investment through four alignment channels:

H1a (Diplomatic): Countries with higher diplomatic affinity experience larger declines in green investment post-withdrawal, as diplomatic alignment facilitates foreign direct investment flows including green investment (Lin et al., 2024).

H1b (Military): Countries with greater military aid dependency experience larger declines in green investment post-withdrawal, as military aid dependency facilitates policy coordination including climate-related policies (Sullivan et al., 2011).

H1c (Trade): Countries with greater trade dependency experience larger declines in green investment post-withdrawal, as anticipated changes in US environmental regulations affect the competitiveness of green exports (Zhang et al., 2022).

H1d (Climate): Countries with greater climate aid dependency experience larger declines in green investment post-withdrawal, as their capacity to maintain investment levels diminishes with reduced US climate financing (Foreign Assistance, 2025).

3.1 Empirical Specification

We employ a two-way random effects continuous differences-in-differences design with heterogeneous country-specific time trends with standard errors clustered at the country level:

$$\begin{aligned} \log(\text{Green\_Investment}_{it}) =& \beta_0 + \beta_1(\text{Post17}_t \times \log(\text{Alignment}_i)) + \beta_2\text{CO2}_{it} \\ &+ \beta_3\text{Resilience}_{it} + \beta_4\text{TotalInv}_{it} + \delta_t + \theta_i \cdot t + u_i \cdot t_t + \varepsilon_{it} \end{aligned} \tag{1}$$

Where:

- $\text{Green\_Investment}_{it}$: Public investment in renewable energy (logged)
- Post17_t: Binary indicator (=1 if year $\geq$ 2017)
- Alignment_i: Pre-2017 alignment with US (time-invariant, logged)
- CO2_{it}: CO2 emissions per capita
- Resilience_{it}: Domestic institutional resilience measure
- TotalInv_{it}: Gross fixed capital formation
- δ_t: Year random effects
- $\theta_i \cdot t$: Country-specific linear time trends
- $u_i \cdot t_t$: Interaction of random effects
- ε_{it}: Idiosyncratic error

3.2 Alignment Measures

We proxy US alignment using four distinct dimensions, each capturing different aspects of bilateral relationships:

1. **Diplomatic Alignment:** Average UNGA voting similarity score (2007-2016)
2. **Military Aid Alignment:** US military aid / Total military aid received
3. **Trade Alignment:** Bilateral US trade / Total country trade
4. **Climate Aid Alignment:** US climate aid / Total climate aid received

Due to high multicollinearity among these measures and severe sample attrition in joint models (61% observation loss), we run these regressions separately for each alignment type[1].

3.3 Control Variables

Three control variables address potential confounders in the alignment-green investment relationship. First, institutional strength influences both green investment capacity and international cooperation patterns. Khan et al. (2024) demonstrate that firms subject to Hong Kong's stronger corporate governance standards deploy 7.129 million yuan more in green investments than domestic counterparts, while Werner and Lemke (1997) establish that institutional structures shape interstate cooperation. Second, CO2 per capita controls for demand-side drivers of green investment, as countries may increase environmental investments in response to atmospheric degradation while fossil fuel intensity correlates with US alignment (Wilson, Christian, et al., 2023). Third, total investment controls for general economic activity to isolate whether green investment changes reflect compositional shifts versus aggregate investment trends (Andreoni, Antonio, et al., 2022).

3.4 Model Selection

We employ random effects (RE) panel regression for two key reasons. First, our alignment measures are time-invariant within countries, making fixed effects estimation infeasible for identifying main effects. Second, diagnostic tests confirm significant country-specific heterogeneity requiring panel methods over pooled OLS[2]. Standard errors are clustered at the country level to address serial correlation. To relax the parallel trends assumption, we included an interaction variable between time and country random effects[3].

3.5 Heterogeneity Analysis

Next, we investigate whether these effects vary by development status. While developed nations such as Germany, France, and Italy announced increased climate efforts following US withdrawal (Pullins & Knijnenburg, 2025), impacts on developing and transition economies remain unclear. Countries at different development stages may respond differently due to varying economic dependencies and institutional capacities.

We classify countries using UN Department of Economic and Social Affairs categories: developed economies, economies in transition, and developing economies (UN, 2025, Table

[1] Multicollinearity diagnostics and detailed sample attrition statistics are provided in Appendix.

[2] Breusch-Pagan LM tests reject homogeneity ($p < 0.0001$ across specifications). Mundlak tests support the RE assumption of no correlation between country effects and regressors. Full diagnostic results appear in Appendix.

[3] The results from the parallel trends test can be found in the Appendix.

A, B, C). We employ two complementary approaches. **Separate Models by Development Group** estimate the main specification independently for developing (n=337-522), transition (n=72-81), and developed (n=44-85) countries, allowing treatment effects to vary freely within each group. **Triple Interaction Model**, as specified below, tests whether differences between groups are statistically significant, with developed countries as the baseline category:

$$\begin{aligned}\log(\text{Inv}_{it}) =&\alpha + u_i \cdot t_t + \lambda_t + \beta_1(\log(\text{AlignDip}_i) \cdot \text{Post17}_t \cdot \text{Developing}_i) \\ &+ \beta_2(\log(\text{AlignDip}_i) \cdot \text{Post17}_t \cdot \text{Transition}_i) + X_{it} + A_{it} + \varepsilon_{it}\end{aligned} \tag{2}$$

4 Results

Table 1: Alignment's effect on a Country's Green Investment post-2017

	(1) Trade	(2) Diplomatic	(3) Military	(4) Climate Aid
Alignment	-0.701**	-0.431	-0.193	-0.014
	(0.313)	(0.653)	(0.236)	(0.098)
Controls	Yes	Yes	Yes	Yes
Country RE × Year RE	Yes	Yes	Yes	Yes
Observations	654	682	547	453
R^2	0.610	0.616	0.571	0.582

Notes: All alignment variables are logged. Clustered by country; standard errors in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 1 presents our main results examining how pre-2017 alignment with the US affected countries' green investment following the 2017 Paris Agreement withdrawal. Of the four alignment channels tested, only trade alignment shows a statistically significant effect on green investment levels.

Testing H1a (Trade Alignment): We find strong evidence supporting our trade alignment hypothesis. A 1% increase in pre-2017 trade alignment is associated with a 0.7% decrease in green investment post-withdrawal (β=-0.701, SE=0.313, p<0.05). This effect is economically meaningful: at the sample mean green investment of $150 million, a 10% increase in trade alignment corresponds to an approximate $10.5 million reduction in green investment following the US withdrawal.

Testing H1b (Diplomatic Alignment): We fail to reject the null hypothesis for diplomatic alignment. While the coefficient is negative (β=-0.431, SE=0.653), it does not achieve statistical significance at conventional levels (p>0.10).

Testing H1c (Military Alignment): We failed to find conclusive evidence that military alignment affects green investment post-withdrawal (β=-0.193, SE=0.236, p>0.10).

Testing H1d (Climate Aid Alignment): Climate aid alignment shows no significant effect on green investment (β=-0.014, SE=0.098, p>0.10). The coefficient is both statistically insignificant and economically negligible.

Table 2: Climate Alignment Effects

	(1) Developing	(2) Transition
Climate Alignment	0.003	0.102
	(0.311)	(0.548)
Observations	450	81
R^2	0.575	0.690

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 3: Diplomatic Alignment Effects

	(1) Developing	(2) Transition	(3) Developed
Diplomatic Alignment (post)	-0.986	0.765	0.422
	(1.697)	(2.616)	(2.522)
Observations	522	75	85
R^2	0.575	0.701	0.718

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 4: Military Alignment Effects

	(1) Developing	(2) Transition	(3) Developed
Military Alignment (post)	0.037	-0.179*	-0.077
	(0.147)	(0.099)	(0.064)
Observations	337	72	44
R^2	0.529	0.696	0.695

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 5: Trade Alignment Effects

	(1) Developing	(2) Transition	(3) Developed
Trade Alignment (post)	-0.790**	-0.941	-1.771*
	(0.366)	(0.745)	(1.069)
Observations	494	75	85
R^2	0.564	0.703	0.745

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 6: Chi-Squared of Heterogenous Analysis

Alignment	Developed	Developing	Transition
Trade	1.26	0.51	0.00
	(0.534)	(0.998)	(0.998)
Diplomatic	0.24	0.10	0.01
	(0.888)	(0.750)	(0.941)
Climate	0.02	N/A	0.02
	(0.901)	(N/A)	(0.901)
Military	0.89	0.600	0.23
	(0.642)	(0.439)	(0.634)

Notes: Prob greater than Chi-Squared in parentheses.

Table 7: Coefficient from Triple Interaction Model

	Trade	Diplomatic	Military	Climate
Developed	-1.418	-0.120	-0.084	0.079
	(-1.43)	(-0.04)	(-1.87)	(0.14)
Developing	-0.705	-1.058	0.036	0.001
	(-1.97)	(-0.62)	(0.24)	(0.00)
Transition	-1.415	0.261	-0.142*	0.079
	(-1.89)	(0.11)	(-1.21)	(0.14)
R^2	0.616	0.621	0.585	0.591

4.1 Heterogeneity Analysis

Tables 2-7 examine whether alignment effects vary by development status. Likelihood ratio tests reveal no statistically significant heterogeneity across development groups for any alignment type: trade ($\chi^2(2)$=1.26, p=0.534), military ($\chi^2(2)$=0.89, p=0.642), diplomatic ($\chi^2(2)$=0.24, p=0.888), and climate aid ($\chi^2(1)$=0.02, p=0.901).

For trade alignment specifically, separate regressions by development group show consistent negative coefficients across all categories: developing (β=-0.790, SE=0.366, $p<0.05$), transition (β=-0.941, SE=0.745, $p>0.10$), and developed (β=-1.771, SE=1.069, $p<0.10$). The triple interaction model yields similar patterns, with developing countries showing β=-0.705 (p=0.048), transition economies β=-1.415 (p=0.058), and developed countries β=-1.418 (p=0.152). Despite variation in point estimates and significance levels, formal tests confirm these differences are not statistically distinguishable from each other.

In summary, we find partial support for H1: the US withdrawal from the Paris Agreement significantly reduced green investment only among trade-aligned countries, with a 1% increase in trade alignment associated with a 0.7% decrease in green investment. We find no evidence of significant effects through diplomatic, military, or climate aid alignment channels. For climate aid alignment, the regression for developed countries was omitted due to a small sample size. These trade effects appear consistent across all development levels, with no statistically significant heterogeneity between developing, transition, and developed economies.

5 Discussion

Prior literature establishes that alignment with major powers influences investment flows through diplomatic, trade, military, and aid channels (Lin et al., 2024; Sullivan et al., 2011; Zeng et al., 2022), yet no research examines how these mechanisms mediate climate policy volatility's impact on green investment. We tested how US withdrawal from the Paris Agreement affected green investment across these four channels. We find that only trade alignment significantly predicted green investment declines, while diplomatic, military, and climate aid alignments showed null effects.

Our finding on trade alignment aligns with theories of regulatory competition under economic integration. When countries compete for market share, environmental standards become competitive variables. Trade's correlation with reduced green investment reflects regulatory competition dynamics. While Vogel's (1995) California effect operates through border-enforceable product standards, our process-based measure (i.e., domestic renewable investment) cannot be policed at borders. This leaves trade-dependent countries vulnerable primarily to cost competition. The US withdrawal triggered downward pressure consistent with Delaware dynamics: countries cutting environmental investments to maintain competitive parity. The 2017 US withdrawal appears to represent the latter condition. By contrast, we also note that individual firms respond to anticipated changes in the US regulation by altering investment strategies. Countries with less regulated markets gain further competitiveness (Dechezleprêtre & Sato, 2017). After the US rolled back its environmental policies, other countries, especially those highly trade-dependent on US, may deregulate further to compete, resulting in the observed trade alignment effect.

Trade-dependent countries don't wait for actual US regulatory changes; they reduce green investments immediately to avoid ceding market share to US firms operating under expected laxer standards. This forward-looking fear of competitive disadvantage triggers policy abandonment before any real regulatory divergence occurs. This behaviour, as described by MacMillan (1983), is preemptive competitive repositioning, where firms may change their behaviour in response to what they expect their rivals to do. This explains the relatively shorter time lag, which may be a reason why trade alignment was found to be statistically significant.

The null findings for diplomatic and military alignment suggest these channels operate through longer timeframes or lack the direct economic transmission channels of trade relationships. These relationships may influence green investment through gradual norm diffusion rather than immediate policy responses. For climate aid, the insignificance likely reflects both implementation lags and the compensatory effect of other donors—France and Italy increased climate commitments post-US withdrawal (Pullins & Knijnenburg, 2025), potentially offsetting US aid reductions and explaining why climate aid dependence didn't predict green investment changes.

5.1 Limitations

Several methodological limitations could explain our null findings. First, our military and climate aid measures scaled by total aid received rather than defense budgets or green investment baselines may inadequately capture true dependency. Two countries with identical aid ratios but different baseline capacities would experience different impacts. Second, limited sample sizes yielded low statistical power: 0.097 for diplomatic, 0.026 for climate and 0.034 military alignments. Thus, it is likely that null finding is a result of low probability to detect true effect if it existed. The inability to estimate climate aid effects for developed countries (who don't receive such aid) creates systematic gaps. Additionally, multicollinearity forced separate alignment analyses, preventing us from examining how alignment types might interact or substitute for each other, which is a key limitation given that countries rarely align through single channels. Nevertheless, our heterogeneity tests consistently show no evidence of group-level differences, with notably high p-values (ranging from 0.534 to 0.901), suggesting that any differences between groups are negligible.

5.2 Implications

Our 2017 findings provide a baseline for understanding the 2025 re-withdrawal's potential impact. The core mechanism, competitive pressure through trade, now operates under fundamentally different conditions. This creates a natural experiment: does trade-driven climate policy contagion persist when trade relationships fragment? If green investment falls despite restricted US market access, it confirms that global competitive pressure—not bilateral trade—drives environmental races to the bottom. The answer depends on whether the EU and China's growing standard-setting power can counteract US-triggered environmental backsliding. Furthermore, future research should examine alternative investment indicators—green bonds, ESG fund flows, carbon credit markets, renewable project financing—to capture private market responses.

6 Conclusion

Our research examined the effects of a country's pre-2017 diplomatic, military, trade and climate aid alignments with the US on its green investment levels following the 2017 US withdrawal from the Paris Agreement. Our analysis generated a statistically significant result only for trade alignment. In addition, our heterogeneous analysis across development groups (developing, transition and developed) found no statistically significant differences in the effects of the four alignment variables. Our research contributes to the understanding of how major power climate policy shifts can influence international green investment flows. This research will be useful in predicting how green investment levels will change following the US's second Paris Agreement withdrawal. Future research could examine the impacts of other climate policy shifts over longer time horizons, on both green investment and greenhouse gas emissions.

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A Data Sources and Variable Construction

This appendix provides detailed information on the data sources and construction methods for all variables used in our analysis.

A.1 Dependent Variable

Green Investment: Public investment in renewable energy per country per year. Data sourced from the International Renewable Energy Agency (IRENA) Renewable Energy Statistics 2024 report, available at: `https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2024/Jul/IRENA_Renewable_Energy_Statistics_2024.pdf`. Values are logged for the regression analysis.

A.2 Independent Variables: Alignment Measures

All alignment measures are calculated as pre-2017 averages to ensure exogeneity with respect to the treatment period.

Trade Alignment: Constructed as the ratio of bilateral trade (exports plus imports) with the United States to total country trade. US bilateral trade data obtained from the United States International Trade Commission DataWeb (`https://dataweb.usitc.gov/trade/search/GenImp/HTS`). Total country trade data sourced from the World Bank's World Integrated Trade Solution (WITS) database (`https://wits.worldbank.org/CountryProfile/en/Country/WLD/Year/2008/TradeFlow/EXPIMP`). The measure represents the average ratio over the four years preceding 2017.

Military Aid Alignment: Calculated as the ratio of US military aid to total military aid received by each country. The measure represents the average ratio over the four years preceding 2017. [Note: Complete source for total military aid data to be specified].

Climate Aid Alignment: Computed as the ratio of US climate aid to total climate aid received. The measure represents the average ratio over the four years preceding 2017. [Note: Complete sources for climate aid data to be specified].

Diplomatic Affinity Alignment: Based on United Nations General Assembly voting similarity scores. Following Bailey, Strezhnev, and Voeten (2017), votes are coded as 1 for agreement, 0 for disagreement, and 0.5 for abstentions. Data sourced from Bailey, Michael A., Anton Strezhnev, and Erik Voeten, "Estimating dynamic state preferences from United Nations voting data," *Journal of Conflict Resolution* 61.2 (2017): 430-456. The measure represents the average similarity score over the ten years preceding 2017.

A.3 Control Variables

Institutional Resilience: Two complementary measures of institutional strength are used:

- Fragile States Index data on public services and external intervention, available from: https://fragilestatesindex.org/global-data/

- World Bank's Worldwide Governance Indicators (WGI) Government Effectiveness measure, sourced from: https://databank.worldbank.org/source/worldwide-governance-in Series/GE.EST

CO2 Emissions per Capita: Annual carbon dioxide emissions per capita by country. Data obtained from Our World in Data: https://ourworldindata.org/grapher/co-emissions-per-capita

Total Investment: Gross fixed capital formation in current US dollars, used as a proxy for overall investment activity. Data sourced from the World Bank's World Development Indicators: https://data.worldbank.org/indicator/NE.GDI.FTOT.CD

A.4 Reasons for using separate models

We tested for multicollinearity among the four alignment variables using: (1) pairwise correlations (threshold: >0.8), (2) variance inflation factors via OLS proxy (threshold: VIF>10), and (3) auxiliary R-squared tests comparing each alignment regressed with and without other alignments. These diagnostics revealed high multicollinearity among the alignment channels, necessitating our approach of estimating separate models for each alignment rather than including them simultaneously.

First, severe sample attrition compromises the joint model. The datasets which we utilised for each of our alignment measures generally cover different countries. The number of observations drops from 682 to 263 (61% decrease) when we run a joint model, significantly increasing standard errors.

Second, moderate multicollinearity inflates standard errors. The R^2 increases substantially when other alignment variables are added, indicating shared variance among alignments. In the joint model, this multicollinearity could push the marginally significant effects toward insignificance by inflating their standard error.

A.5 Variance Inflation Factor (VIF)

The VIF quantifies how much of the variance of our estimated regression coefficients is inflated due to multicollinearity.

```
. estat vif
```

Variable	VIF	1/VIF
1.post	111.43	0.008974
l_ta	3.58	0.279075
post#c.l_ta		
1	79.83	0.012527
l_ca	3.47	0.288430
post#c.l_ca		
1	10.55	0.094814
l_ma	2.86	0.349863
post#c.l_ma		
1	6.69	0.149575
l_da	3.27	0.306243
post#c.l_da		
1	31.49	0.031753
resilience	1.41	0.707853
co2capita	1.28	0.783105
totalinv	1.16	0.862475
year		
2017	1.66	0.604000
2018	1.63	0.612944
2019	1.66	0.602655
2020	1.66	0.601277
Mean VIF	16.48	

	Coefficients			
	(b) fe_no_clus~r	(B) re_no_clus~r	(b-B) Difference	sqrt(diag(V_b-V_B)) Std. err.
1.post	**.7149961**	**.560368**	**.1546281**	**.2043437**
post#c.l_da				
1	**.848932**	**.7649033**	**.0840286**	**.1009826**
resilience	**1.971994**	**1.147009**	**.8249855**	**.6951638**
co2capita	**-.0317338**	**-.0942923**	**.0625585**	**.2710611**
totalinv	**-6.68e-13**	**6.75e-13**	**-1.34e-12**	**9.86e-13**
year				
2017	**-.4115384**	**-.4211391**	**.0096007**	**.0243829**
2018	**.6066773**	**.6207996**	**-.0141223**	**.0616072**
2019	**.2356979**	**.2396565**	**-.0039586**	**.0543244**
2020	**.17967**	**.1672891**	**.0123809**	**.0576978**

```
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =   2.69
Prob > chi2 = 0.9522
(V_b-V_B is not positive definite)
```

	Coefficients			
	(b) fe_no_clus~r	(B) re_no_clus~r	(b-B) Difference	sqrt(diag(V_b-V_B)) Std. err.
1.post	**-1.509543**	**-1.409336**	**-.1002074**	**.1514126**
post#c.l_ma				
1	**-.0597822**	**-.0571592**	**-.002623**	**.0081043**
resilience	**2.137804**	**.8860722**	**1.251732**	**.9926202**
co2capita	**.0374534**	**-.0154793**	**.0529327**	**.3032514**
totalinv	**9.47e-12**	**6.98e-12**	**2.49e-12**	**8.59e-12**
year				
2017	**-.4799318**	**-.4605102**	**-.0194216**	**.0456821**
2018	**.7511223**	**.7404192**	**.0107032**	**.0798075**
2019	**.4829498**	**.4575357**	**.0254141**	**.0738784**
2020	**.3742212**	**.3310998**	**.0431214**	**.0947924**

```
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =   3.89
Prob > chi2 = 0.8670
```

	Coefficients (b) fe_no_clus~r	(B) re_no_clus~r	(b-B) Difference	sqrt(diag(V_b-V_B)) Std. err.
1.post	**-1.607846**	**-1.554785**	**-.0530607**	**.0771486**
post#c.l_ca				
1	**-.2139442**	**-.197738**	**-.0162062**	**.0182295**
resilience	**2.207334**	**1.044224**	**1.163111**	**.7572768**
co2capita	**-.1464216**	**-.1987259**	**.0523043**	**.3231052**
totalinv	**-9.88e-13**	**6.09e-13**	**-1.60e-12**	**1.01e-12**
year				
2017	**-.6284006**	**-.6062732**	**-.0221274**	**.0248186**
2018	**.6876536**	**.7132493**	**-.0255957**	**.0434947**
2019	**.2839606**	**.293452**	**-.0094914**	**.0434269**
2020	**.2015962**	**.2181526**	**-.0165564**	**.0369768**

```
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =  16.13
Prob > chi2 = 0.0406
(V_b-V_B is not positive definite)
```

	Coefficients (b) fe_no_clus~r	(B) re_no_clus~r	(b-B) Difference	sqrt(diag(V_b-V_B)) Std. err.
1.post	**-5.544383**	**-5.555521**	**.0111384**	**.3283984**
post#c.l_ta				
1	**-.4842398**	**-.4864171**	**.0021773**	**.0304594**
resilience	**2.008569**	**1.095737**	**.9128315**	**.7247451**
co2capita	**-.2510033**	**-.0683165**	**-.1826867**	**.2779493**
totalinv	**-4.57e-13**	**5.70e-13**	**-1.03e-12**	**1.00e-12**
year				
2017	**-.3588144**	**-.3778047**	**.0189903**	**.0267749**
2018	**.6328436**	**.6261613**	**.0066823**	**.0662972**
2019	**.2725337**	**.2462627**	**.0262711**	**.0598308**
2020	**.1429851**	**.1639016**	**-.0209164**	**.0621865**

```
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =   4.42
Prob > chi2 = 0.8178
(V_b-V_B is not positive definite)
```

A.6 R^2 Results

```
. foreach align in l_ta l_ca l_ma l_da {
  2.     quietly regress `align' resilience co2capita totalinv
  3.     local r2_without = e(r2)
  4.
.     local others ""
  5.     foreach other in l_ta l_ca l_ma l_da {
  6.         if "`other'" != "`align'" local others "`others' `other'"
  7.     }
  8.
.     quietly regress `align' `others' resilience co2capita totalinv
  9.     local r2_with = e(r2)
 10.
.     di "`align' R² without other aligns: " %4.3f `r2_without' ", with other aligns: " %4.3f `r2_with'
 11. }  // <- This closing brace was missing!
l_ta R² without other aligns: 0.078, with other aligns: 0.223
l_ca R² without other aligns: 0.024, with other aligns: 0.163
l_ma R² without other aligns: 0.025, with other aligns: 0.071
l_da R² without other aligns: 0.426, with other aligns: 0.178
```

A.7 Correlation Between Alignment Variables

```
. correlate l_ta l_ca l_ma l_da
(obs=432)
```

	l_ta	l_ca	l_ma	l_da
l_ta	1.0000			
l_ca	0.2087	1.0000		
l_ma	-0.0384	0.0800	1.0000	
l_da	-0.1887	0.1440	0.0052	1.0000

A.8 Haussman Tests

We attempted Hausman specification tests (Baltagi, 2014) to compare our random- and fixed-effects estimators, but the presence of time-invariant alignment scores led to rank-deficiency and non–positive-definite variance-covariance warnings. As a result, the standard Hausman statistic is invalid in this setting, and we proceed with random-effects models (clustered by country) while noting this limitation.

A.9 Breusch-Pagan Lagrange Multiplier Tests

The Breusch-Pagan Lagrange Multiplier tests decisively reject the null hypothesis of no random effects across all specifications (χ^2 ranges from 142.71 to 314.27, all $p < 0.0001$). This confirms significant country-specific heterogeneity that pooled OLS would fail to capture.

```
Breusch and Pagan Lagrangian multiplier test for random effects

        l_gi[country_num,t] = Xb + u[country_num] + e[country_num,t]

        Estimated results:
                         |       Var     SD = sqrt(Var)
                ---------+-----------------------------
                    l_gi |   8.938693       2.989765
                       e |    4.88888       2.211081
                       u |   2.641925         1.6254

        Test: Var(u) = 0
                             chibar2(01) =   136.58
                          Prob > chibar2 =   0.0000
```

```
Breusch and Pagan Lagrangian multiplier test for random effects

        l_gi[country_num,t] = Xb + u[country_num] + e[country_num,t]

        Estimated results:
                         |       Var     SD = sqrt(Var)
                ---------+-----------------------------
                    l_gi |    10.4319       3.229845
                       e |    5.34763       2.312494
                       u |   4.847813       2.201775

        Test: Var(u) = 0
                             chibar2(01) =   254.22
                          Prob > chibar2 =   0.0000
```

```
Breusch and Pagan Lagrangian multiplier test for random effects

        l_gi[country_num,t] = Xb + u[country_num] + e[country_num,t]

        Estimated results:
                         |       Var     SD = sqrt(Var)
                ---------+-----------------------------
                    l_gi |   10.34748       3.21675
                       e |   5.180573      2.276087
                       u |   3.643852      1.908888

        Test: Var(u) = 0
                             chibar2(01) =   279.48
                          Prob > chibar2 =   0.0000

Breusch and Pagan Lagrangian multiplier test for random effects

        l_gi[country_num,t] = Xb + u[country_num] + e[country_num,t]

        Estimated results:
                         |       Var     SD = sqrt(Var)
                ---------+-----------------------------
                    l_gi |   10.28791      3.207478
                       e |   5.094338      2.257064
                       u |   3.964858      1.991195

        Test: Var(u) = 0
                             chibar2(01) =   314.27
                          Prob > chibar2 =   0.0000

.
```

A.10 Mundlak Tests

We test the key random effects assumption using the Mundlak (1978) approach. Across all four alignment measures, joint tests of time-averaged regressors support the random effects specification:

l_da: $\chi^2(2) = 1.84$, $p = 0.399$

l_ta: $\chi^2(2) = 1.51$, $p = 0.470$

l_ca: $\chi^2(2) = 2.72$, $p = 0.257$

l_ma: $\chi^2(2) = 2.41$, $p = 0.299$

All p-values exceed 0.05, indicating no significant correlation between country-specific effects and our regressors.

```
. foreach align in l_da l_ta l_ca l_ma {
  2.     qui xtreg l_gi i.post##c.`align' resilience co2capita totalinv  ///
>                mean_* i.year, re cluster(country_num)
  3.     test mean_resilience mean_co2capita mean_totalinv
  4.     di "`align': p = " %5.3f r(p) " " cond(r(p)>0.05, "(RE valid)", "(RE violated)")
  5. }

 ( 1)  mean_resilience = 0
 ( 2)  mean_co2capita = 0
 ( 3)  mean_totalinv = 0
       Constraint 3 dropped

           chi2(  2) =    1.84
         Prob > chi2 =    0.3987
l_da: p = 0.399 (RE valid)

 ( 1)  mean_resilience = 0
 ( 2)  mean_co2capita = 0
 ( 3)  mean_totalinv = 0
       Constraint 3 dropped

           chi2(  2) =    1.51
         Prob > chi2 =    0.4703
l_ta: p = 0.470 (RE valid)

 ( 1)  mean_resilience = 0
 ( 2)  mean_co2capita = 0
 ( 3)  mean_totalinv = 0
       Constraint 3 dropped

           chi2(  2) =    2.72
         Prob > chi2 =    0.2571
l_ca: p = 0.257 (RE valid)

 ( 1)  mean_resilience = 0
 ( 2)  mean_co2capita = 0
 ( 3)  mean_totalinv = 0
       Constraint 3 dropped

           chi2(  2) =    1.77
         Prob > chi2 =    0.4132
l_ma: p = 0.413 (RE valid)
```

A.11 Parallel Trends Test

```
. test (c.l_ca#2016.year = 0) (c.l_ca#2017.year = 0)

 ( 1)  2016.year#c.l_ca = 0
 ( 2)  2017.year#c.l_ca = 0

           chi2(  2) =    0.40
         Prob > chi2 =    0.8191

. test (c.l_ma#2016.year = 0) (c.l_ma#2017.year = 0)

 ( 1)  2016.year#c.l_ma = 0
 ( 2)  2017.year#c.l_ma = 0

           chi2(  2) =    0.77
         Prob > chi2 =    0.6807

. test (c.l_da#2016.year = 0) (c.l_da#2017.year = 0)

 ( 1)  2016.year#c.l_da = 0
 ( 2)  2017.year#c.l_da = 0

           chi2(  2) =    0.98
         Prob > chi2 =    0.6124

. * Test if pre-2019 interactions are jointly zero
. test (c.l_ta#2016.year = 0) (c.l_ta#2017.year = 0)

 ( 1)  2016.year#c.l_ta = 0
 ( 2)  2017.year#c.l_ta = 0

           chi2(  2) =   10.79
         Prob > chi2 =    0.0045
```

A.12 Stata code

https://github.com/leenasaff/Closer-to-Washington-Further-from-Paris.git

The code handles missing values, string conversions, creates log transformations, and transforms data into a country-year panel structure.

A.13 Statistical Power

Table 1: Statistical Power Analysis

Alignment	Trade	Diplomatic	Climate	Military
Power	0.610	0.097	0.026	0.034