ONLINE APPENDIX

Table A1. Sample distribution by MNE industries

Industry	Firm-Year Observation Proportion
Electronic and other electrical equipment	20.54%
Chemicals and allied products	16.55%
Machinery and equipment	15.26%
Scientific and other instruments	11.10%
Services	6.86%
Transportation equipment	6.50%
Oil and gas	2.46%
Metal products	1.96%
Food and beverage	1.91%
Paper and allied products	1.52%
Communications	1.36%
Iron and steel	1.33%
Household furniture	1.28%
Rubber and plastic products	1.18%
Miscellaneous manufacturing (toys, jewelry, sporting goods, etc.)	0.98%
Petroleum and coal products	0.97%
Glass, cement, clay/stone products	0.86%
Services - Engineering, accounting, research, management	0.68%
Trading	0.66%
Non-Operating Establishments	0.64%
Insurance	0.57%
Mining and quarrying of nonmetallic minerals	0.52%
Tobacco and tobacco products	0.49%
Healthcare	0.47%
Textile	0.46%
Retail, home building materials	0.43%
Publishing	0.42%
Investment	0.41%
Wholesale, durable goods	0.38%
Lumber and wood products	0.28%
Retail, miscellaneous	0.19%
Agriculture, forestry and fishing	0.16%
Heavy construction	0.16%
Utilities	0.11%
Banking	0.11%

Wholesale, non-durable goods	0.09%
Entertainment	0.07%
Retail, food services	0.04%
Education	0.04%

Note: This table shows the sample distribution by MNE industries based on the two-digit Standard Industry Classification (SIC) system.

Table A2. Sample distribution by MNE home and host countries

Panel A. Home country distribution	
Home Country	Firm-Year Observation Proportion
United States	95.93%
Ireland	1.82%
United Kingdom	0.96%
Singapore	0.36%
Switzerland	0.35%
Canada	0.22%
Netherlands	0.16%
Iceland	0.09%
Sweden	0.09%
China	0.03%
Panel B. Host country distribution	
Host Country	Firm-Year Observation Proportion
United States of America	15.25%
United Kingdom	5.72%
Canada	5.16%
Germany	3.57%
Netherlands	3.42%
France	3.17%
Australia	2.91%
China	2.88%
Mexico	2.88%
Singapore	2.61%
Japan	2.48%
Brazil	2.36%
Italy	2.28%
India	2.10%
Spain	2.00%
Switzerland	1.94%

Ireland	1.86%
Belgium	1.66%
Sweden	1.50%
South Korea	1.44%
Malaysia	1.35%
Luxembourg	1.31%
Argentina	1.19%
Poland	1.17%
Austria	1.05%
Thailand	1.03%
Denmark	1.03%
New Zealand	1.02%
South Africa	1.01%
Chile	0.94%
Barbados	0.94%
Norway	0.87%
Czech Republic	0.83%
Russia	0.82%
Hungary	0.82%
Israel	0.80%
Finland	0.76%
Philippines	0.71%
Portugal	0.69%
Turkey	0.68%
Colombia	0.67%
Venezuela	0.65%
Mauritius	0.62%
Indonesia	0.62%
Peru	0.51%
United Arab Emirates	0.50%
Panama	0.48%
Costa Rica	0.43%
Greece	0.42%
Romania	0.42%
Uruguay	0.38%
Slovakia	0.37%
Cyprus	0.33%
Egypt	0.30%
Guatemala	0.28%
Saudi Arabia	0.28%

Nigeria	0.27%
Ecuador	0.25%
Ukraine	0.25%
Viet Nam	0.23%
Bahamas	0.23%
Dominican Republic	0.20%
Bulgaria	0.20%
Morocco	0.19%
El Salvador	0.17%
Honduras	0.16%
Trinidad and Tobago	0.16%
Jamaica	0.15%
Croatia	0.15%
Malta	0.14%
Kenya	0.14%
Pakistan	0.14%
Slovenia	0.13%
Bolivia	0.13%
Serbia	0.13%
Kazakhstan	0.12%
Estonia	0.12%
Latvia	0.12%
Lithuania	0.11%
Bahrain	0.10%
Nicaragua	0.10%
Others	2.31%

Note: This table shows the sample distribution by MNE home countries (Panel A) and host countries (Panel B). For brevity, “others” in Panel B includes 105 host countries, each of which accounts for less than 0.10% of firm-year observations in our sample.

Raw Data Patterns and Trends

Figure A1 shows the time trend of climate innovation focus of the MNEs in our sample from 1995 to 2017. We note that there has been an increasing trend in climate innovation focus since 2000.

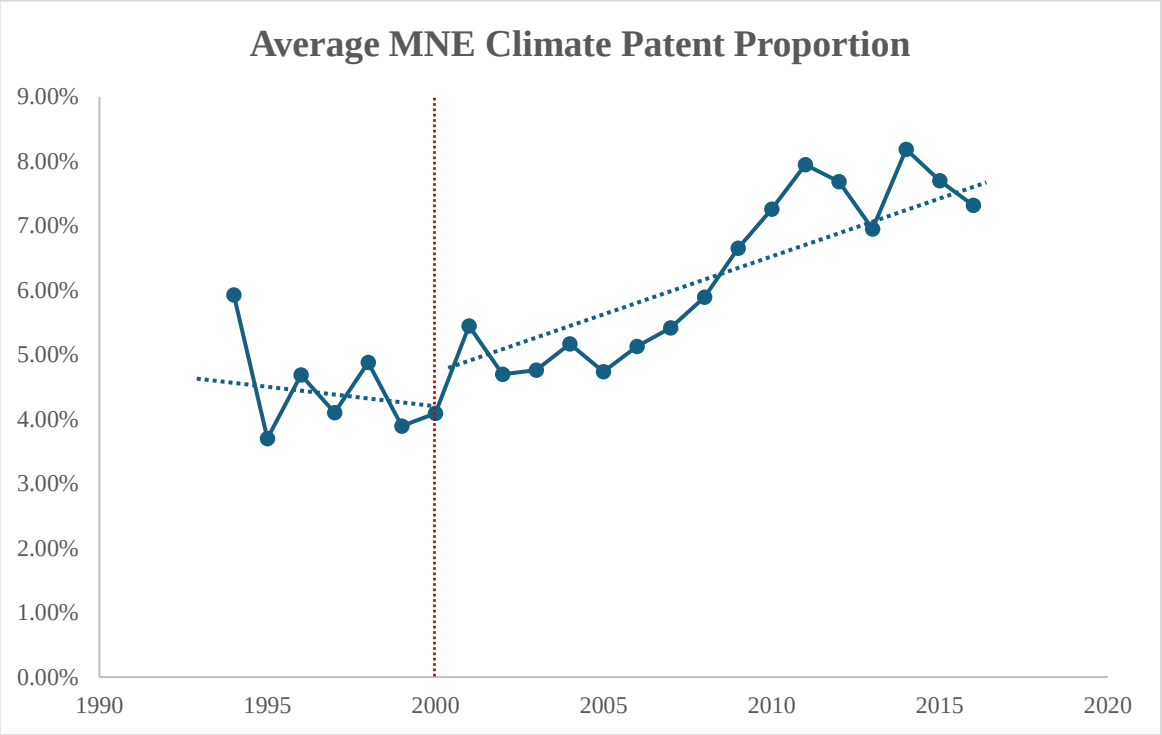

Figure A1. Time trend of MNE climate innovation focus

This figure shows the average level of MNE climate innovation indicated by the proportion of climate mitigation and adaptation patents in an MNE's total patents in a year from 1995 to 2017 in our sample.

Figure A2 shows the global annual frequencies of severe climate-related natural disasters from IMF's Climate Change Dashboard. There is an increasing trend in the occurrence of natural disasters globally. The average annual level of all climate-related natural disasters appears elevated after the year 2000 compared to before. Severe storm demonstrates the highest frequency in most record years, followed by landslide and flood. Importantly, these types of disasters can impose operational disturbances and economic losses across a wide variety of industries.

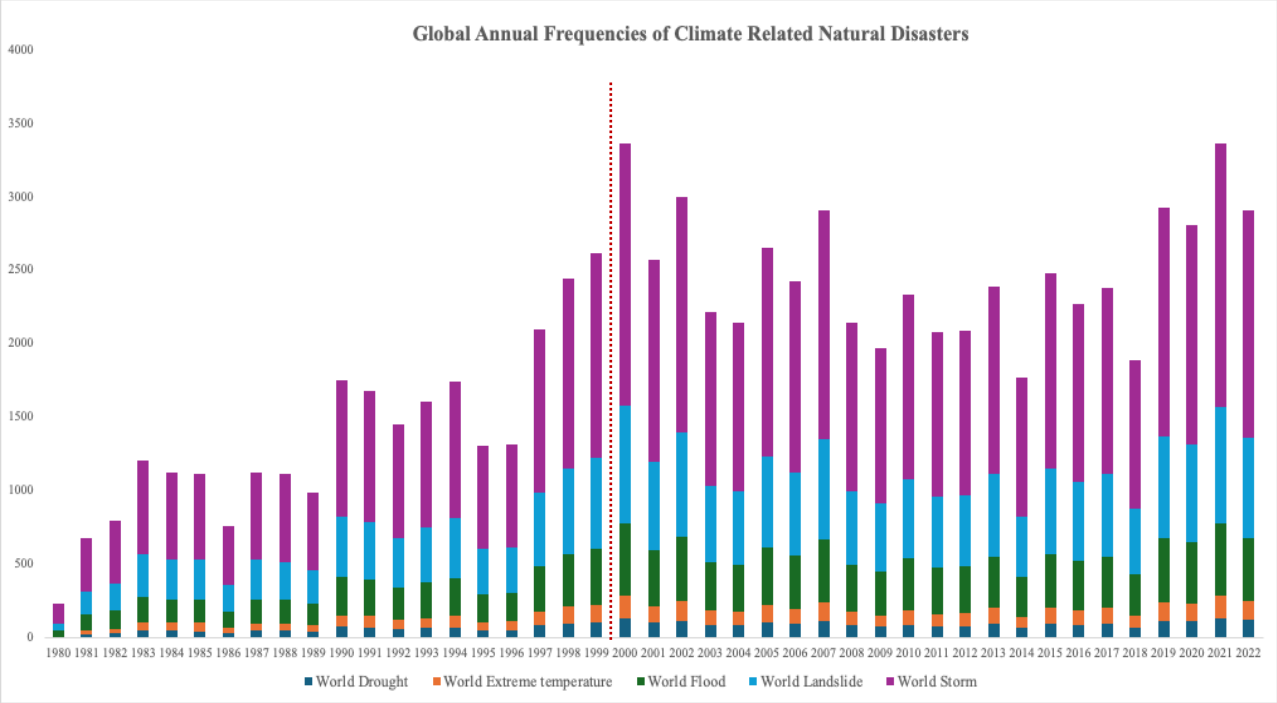

Figure A2. Annual frequencies of climate-related natural disasters worldwide

This figure shows the frequencies of severe climate-related natural disasters that occurred in each year globally. (i.e., combining all countries in the International Monetary Fund's Climate Change Dashboard records), including drought, extreme temperature, flood, landslide, and storm.

Figure A3 shows the time trends of country-level *climate policy index* and *societal vulnerability score*—which underline our moderators, *regulatory demand* and *societal demand*, respectively—of the top five developed and developing countries ranked by the percentage of MNE operations in our sample. We note that developed countries tend to strengthen climate policies over time, especially since 2008. Among the developing countries, Mexico and Brazil show relatively high levels of climate policy stringency; China and Malaysia appear to have relaxed their climate policies from 2002 to 2008, and India showed a drop in climate policy strength from 2005 to 2012. Regarding societal vulnerability, developing countries are more vulnerable to the adversity of climate change than developed countries as expected, with India showing the highest level of societal vulnerability across the years.

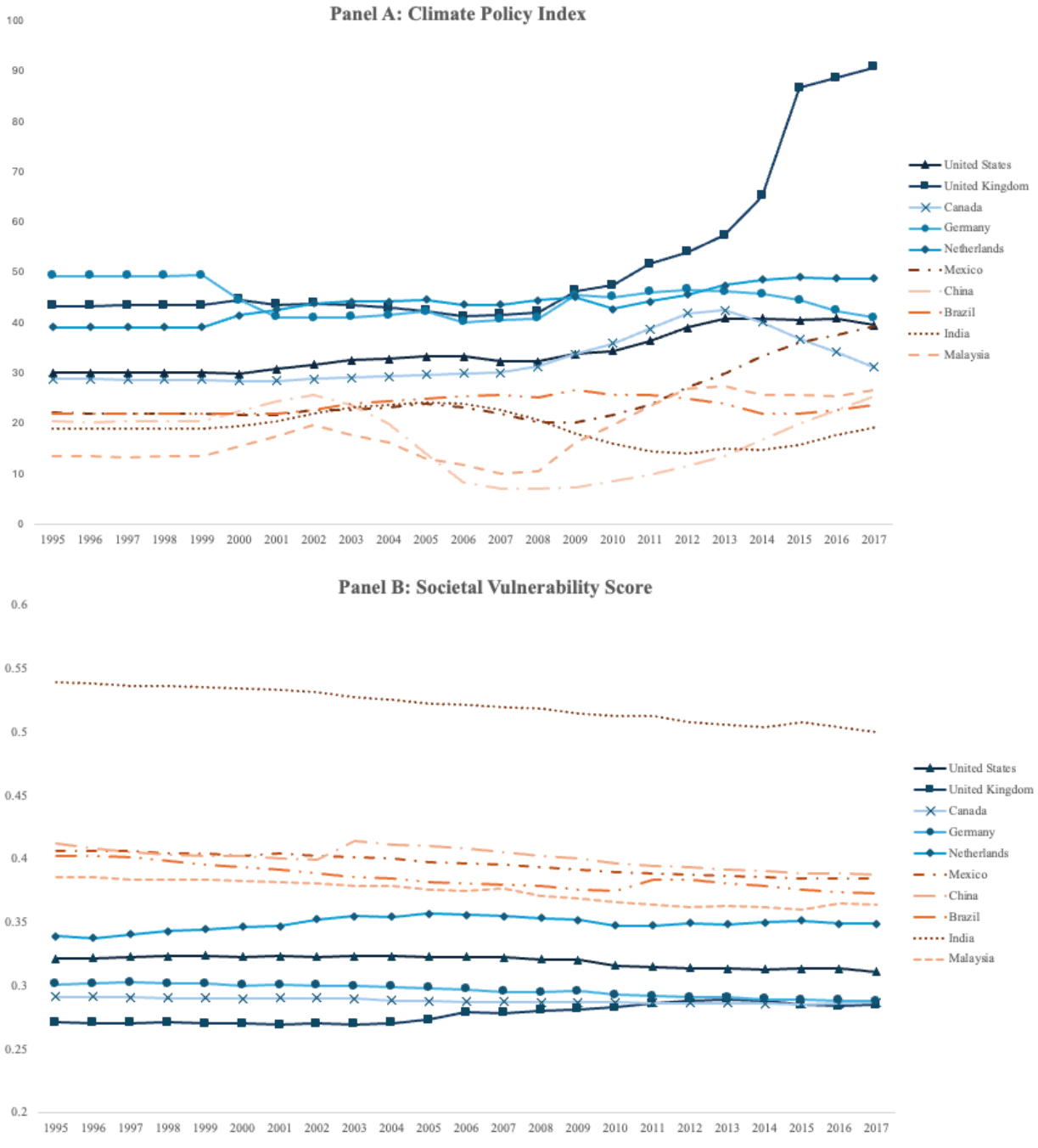

Figure A3. Time trend of country-level climate policy index and societal vulnerability score

This figure shows the annual levels of *climate policy index* from the Environmental Performance Index (EPI) and *societal vulnerability score* from the Notre Dame Global Adaptation Initiative (ND-GAIN) of the top-five developed and developing countries ranked by MNE subsidiary operations in our sample: United States (14.1%), United Kingdom (5.29%), Canada (4.79%), Germany (3.31%), Netherlands (3.17%), Mexico (2.67%), China (2.65%), Brazil (2.18%), India (1.19%), Malaysia (1.25%).

Robustness Tests and Supplemental Analyses

Two-stage instrumental variable analysis. We conduct a two-stage instrumental variable analysis to mitigate endogeneity concerns. Specifically, while the occurrence of natural disasters is exogenous to MNE decisions, the firm's subsidiary portfolio (i.e., how many subsidiaries to maintain in which countries) is an endogenous decision. It is plausible that a focal MNE's climate innovation performance will reversely affect its subsidiary portfolio, thus changing the focal firm's exposure to global climate change risks. Similarly, there may be unobserved factors endogenous to the firm that drive both subsidiary portfolio and climate innovation performance. To address these endogeneity concerns, we regress our independent variable, *climate risk exposure*, on the instrument and all our control variables in the first-stage panel OLS model and then regress our dependent variable, *climate innovation*, on the independent and control variables and the first-stage residual in the second-stage panel Poisson model (Lin & Wooldridge, 2019).

Following prior research on firm exposure to global climate risks, we use MNEs' *home country population density* (i.e., the number of people per square kilometer in country *c* in year *t*, data obtained from the World Bank) as our first instrument for *climate risk exposure* (Huang et al., 2018). The relevance of this instrument is two-fold: first, population density in an MNE's home country can sway its international expansion but will not be reversely affected by the firm's global subsidiary portfolio; second, prior research demonstrates a significant correlation between the population density in a firm's home country and its exposure to global climate risk (Huang et al., 2018). Regarding exclusivity, the population density of each firm's home country is unlikely to directly impact the firm's climate innovation inclination except by first influencing the level of climate risk that the firm experiences (e.g., public infrastructure in countries with high population density may be better developed to offset the potential economic loss burdened by each firm, thus

reducing the urgency to conduct climate innovation at the firm level).[1] Moreover, it is unlikely that firm-level climate innovation performance will materially alter country-level population density.

Our second instrument is *peer climate risk exposure*, calculated as the average score of *climate risk exposure* of a firm's industry (i.e., based on three-digit SIC code) in a year with each focal firm's score excluded. It is reasonable to expect industry peers' climate risk exposure to correlate with that of a focal firm since each firm's internationalization decisions can be driven by industry norms, whereas the decision of each firm alone is unlikely to alter the norms of the entire industry. Furthermore, peer exposure to climate risk is unlikely to directly affect the focal firm's climate innovation except by first altering its own exposure to global climate risks. The results of the instrumental variable tests are reported in Table A3.

In Model 1, we regress *climate risk exposure* on *home country population density* and all control variables in our main analysis. Consistent with prior research (Huang et al., 2018), we find a negative and statistically significant effect of *home country population density* on *climate innovation* (β = -0.0173, p = 0.0000). The Anderson canonical correlation test LM statistic is 20.142 (p = 0.000), which indicates minimal risk of under-identification; the Cragg-Donald Wald F statistic is 20.145 (10% critical value = 16.38), which indicates minimal risk of weak identification. In the corresponding second stage (Model 2), we find a positive and statistically significant effect of *climate risk exposure* on *climate innovation* (β = 1.5006, p = 0.0000), a negative and statistically significant interaction between *climate risk exposure* and *regulatory demand* (β = -0.0856, p = 0.0000), and a positive and statistically significant interaction between *climate risk exposure* and *societal demand* (β = 0.0774, p = 0.0000).

[1] Alternatively, the argument could be made that population density is positively correlated with greenhouse gas emissions in an MNE's home country, thus raising the firm's exposure to climate risk. We thank an anonymous reviewer for this important point. Our two-stage tests are agnostic on the direction in which *home country population density* affects *climate risk exposure* since it does not jeopardize the relevance criterion. Our first-stage result reveals a negative and statistically significant correlation between *home country population density* and *climate risk exposure*, which is consistent with prior research (Huang et al., 2018).

Table A3. Robustness checks: Two-stage instrumental variable analysis

DV Model	Climate risk exposure (i,t) First stage (1)	Climate innovation (i,t+1) Second stage (2)	Climate risk exposure (i,t) First stage (3)	Climate innovation (i,t+1) Second stage (4)
Home country population density (c, t)	-0.0173 (0.0026) [0.0000]			
Peer climate risk exposure (i,t)			0.0480 (0.0062) [0.0000]	
Climate risk exposure (i, t)		1.5006 (0.3233) [0.0000]		0.2136 (0.2880) [0.4583]
Climate risk exposure (i, t) × Regulatory demand (i, t)		-0.0856 (0.0111) [0.0000]		-0.0838 (0.0113) [0.0000]
Climate risk exposure (i, t) × Societal demand (i, t)		0.0774 (0.0118) [0.0000]		0.0722 (0.0119) [0.0000]
First stage residual		-1.4559 (0.3237) [0.0000]		-0.1687 (0.2885) [0.5587]
Constant	-0.0963 (0.1693) [0.5694]		-0.0507 (0.0165) [0.0021]	
Anderson canonical correlation test LM statistic	20.142 (p = 0.0000)		2840.039 (p = 0.0000)	
Cragg-Donald Wald F statistic	20.145 (10% critical value = 16.38)		3837.517 (10% critical value = 16.38)	
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: All regressors are standardized scores; all models include a vector of firm-year controls as specified in the main analysis (control variable coefficient suppressed for brevity); Models 1 and 3 report the first-stage results, where *climate risk exposure* is regressed on the instrument (Model 1: *home country population* density; Model 3: *peer climate risk* exposure) and all control variables as specified in the main analysis in OLS specifications; Models 2 and 4 are the second-stage fixed-effects panel Poisson models with the first-stage residual, independent and control variables included; firm-clustered robust standard errors are in parentheses; p values are in brackets.

In Model 3, we regress *climate risk exposure* on *peer climate risk exposure* and all control variables in our main analysis. As expected, we find that industry peers' exposure to global climate

risk and firm-level risk exposure are positive and significantly correlated (β = 0.0480, p = 0.0000). The Anderson canonical correlation test LM statistic is 2840.039 (p = 0.000), which indicates minimal risk of under-identification; the Cragg-Donald Wald F statistic is 3837.517 (10% critical value = 16.38), which indicates minimal risk of weak identification. In the corresponding second stage (Model 4), we find a positive but statistically insignificant effect from *climate risk exposure* on *climate innovation* (β = 0.2136, p = 0.4583), a negative and statistically significant interaction between *climate risk exposure* and *regulatory demand* (β = -0.0838, p = 0.0000), and a positive and statistically significant interaction between *climate risk exposure* and *societal demand* (β = 0.0722, p = 0.0000). Overall, the instrumental variable tests provide consistent results to our main analysis, thus strengthening the support for our hypotheses.[2]

Restricted samples. Since we observe a more pronounced increase in MNE climate innovation focus since the year 2000, we restrict our sample to observations after the year 2000 and conduct a set of robustness tests (Table A4: Panel A). This is also consistent with NASA records, which show warning signs of an unabated long-term rise in global temperature in the decades after 2000 compared to the 1951-1980 mean level. Additionally, since our sample is predominantly US-headquartered MNEs (i.e., 96% of all firm-year observations), we re-test our hypotheses in a restricted sample of U.S.-headquartered MNEs (Table A4: Panel B). We continue to find consistent support for H1 – H3 in these restricted samples.[3]

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[2] We also note that, relative to the effect size of the full model in our main analysis (i.e., Model 5, Table 3), the instrumented *climate risk exposure* using either instruments (i.e., Model 2 and Model 4) yields larger estimated effects on *climate innovation*, whereas the effect sizes of the interaction terms in the second-stage models are comparable to those in the full model in our main analysis. Inflation in instrumented variable results is common in extant research across different contexts, which indicates downward bias in the estimated effect without using instrumental variable. In our case, the inflated two-stage effects from both instrument triangulate on a substantive downward bias in the estimated 5% increase in climate patenting by an MNE for each standard deviation increase in its exposure to global climate risk. That is, the "true" impact on MNE *climate innovation* from *climate risk exposure* is potentially much larger than 5%.

[3] For US-headquartered MNEs, it is likely that both national-level climate policies (e.g., regulatory pressure from federal government and host countries) and state-level climate policies will influence how each firm's *climate risk exposure* drives *climate innovation*. We thank an anonymous reviewer for this crucial point. To refine the measure for regulatory demand on US MNE climate actions, we obtained the records of state-level climate policies during

Table A4. Robustness checks: observations after the year 2000 or US-headquartered MNEs

Panel A: Shortened time panel (post-2000)				
	DV: Climate innovation (i, t+1)			
Model	**(1)**	**(2)**	**(3)**	**(4)**
Climate risk exposure (i, t)	0.1236	0.0987	0.1010	0.0813
	(0.0221)	(0.0237)	(0.0226)	(0.0248)
	[0.0000]	[0.0000]	[0.0000]	[0.0011]
Climate risk exposure (i, t) × Regulatory demand (i, t)		-0.0767		-0.0822
		(0.0120)		(0.0120)
		[0.0000]		[0.0000]
Climate risk exposure (i, t) × Societal demand (i, t)			0.0564	0.0632
			(0.0131)	(0.0130)
			[0.0000]	[0.0000]
Regulatory demand (i, t)		0.0196		0.0187
		(0.0167)		(0.0182)
		[0.2408]		[0.3053]
Societal demand (i, t)			0.0510	0.0247
			(0.0132)	(0.0143)
			[0.0001]	[0.0832]
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	7351	7351	7351	7351
Panel B: MNEs headquartered in the US				
	DV: Climate innovation (i, t+1)			
Model	**(1)**	**(2)**	**(3)**	**(4)**
Climate risk exposure (i, t)	0.0830	0.0573	0.0684	0.0545
	(0.0175)	(0.0194)	(0.0180)	(0.0205)
	[0.0000]	[0.0032]	[0.0001]	[0.0079]
Climate risk exposure (i, t) × Regulatory demand (i, t)		-0.0707		-0.0764
		(0.0113)		(0.0113)
		[0.0000]		[0.0000]
Climate risk exposure (i, t) × Societal demand (i, t)			0.0648	0.0705
			(0.0118)	(0.0119)
			[0.0000]	[0.0000]
Regulatory demand (i, t)		0.0307		0.0449
		(0.0156)		(0.0166)
		[0.0495]		[0.0069]
Societal demand (i, t)			0.0266	-0.0053
			(0.0123)	(0.0131)
			[0.0300]	[0.6838]
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	8604	8604	8604	8604

Note: All regressors are standardized scores; all models include a vector of firm-year controls as specified in the main analysis (control variable coefficient suppressed for brevity); firm-clustered robust standard errors are in parentheses; p values are in brackets.

1995 – 2017 from the Berkeley California-China Climate Institute's States Climate Action Map, and we weight the variable *regulatory demand* for sub-sample of US MNEs with the number of climate policies in each US MNE's HQ state in a year to indicate the combined political pressure from the state- and federal-level climate policies and those from each MNE's host countries. We find a negative and statistically significant interaction effect (β = -0.0198, p = 0.0869) in support of H2.

Additional controls. To address the concerns over the serially correlated nature of climate innovation performance and the potential influence of firm innovativeness, we include the lagged *climate innovation* and/or *total firm innovation* as additional control variables in the model. *Total firm innovation* is the total patent count a firm receives in each patent application year. We report these results in Table 6. We find that the main effect of *climate risk exposure* and its interaction with *regulatory* and *societal demand* continues to hold when controlling for lagged *climate innovation* (Table A5: Panel A), lagged *total firm innovation* (Table A5: Panel B), and both (Table A5: Panel C).

Table A5. Robustness checks: controlling for lagged climate innovation and/or total firm innovation

Panel A: Controlling for lagged climate innovation				
	DV: Climate innovation (i, t+1)			
Model	**(1)**	**(2)**	**(3)**	**(4)**
Climate risk exposure (i, t)	0.0834	0.0758	0.0673	0.0765
	(0.0169)	(0.0190)	(0.0174)	(0.0200)
	[0.0000]	[0.0001]	[0.0001]	[0.0001]
Climate risk exposure (i, t) × Regulatory demand (i, t)		-0.0467		-0.0525
		(0.0113)		(0.0112)
		[0.0000]		[0.0000]
Climate risk exposure (i, t) × Societal demand (i, t)			0.0853	0.0883
			(0.0116)	(0.0118)
			[0.0000]	[0.0000]
Regulatory demand (i, t)		0.0587		0.0834
		(0.0156)		(0.0166)
		[0.0002]		[0.0000]
Societal demand (i, t)			0.0225	-0.0172
			(0.0121)	(0.0130)
			[0.0645]	[0.1863]
Climate innovation (i, t)	0.0027	0.0027	0.002	0.0028
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	8969	8969	8969	8969

(Table 6 continues)

Panel B: Controlling for lagged total firm innovation DV: Climate innovation (i, t+1)				
Model	**(1)**	**(2)**	**(3)**	**(4)**
Climate risk exposure (i, t)	0.0787 (0.0170) [0.0000]	0.0585 (0.0190) [0.0021]	0.0660 (0.0176) [0.0002]	0.0576 (0.0200) [0.0040]
Climate risk exposure (i, t) × Regulatory demand (i, t)		-0.0562 (0.0112) [0.0000]		-0.0620 (0.0112) [0.0000]
Climate risk exposure (i, t) × Societal demand (i, t)			0.0701 (0.0117) [0.0000]	0.0746 (0.0118) [0.0000]
Regulatory demand (i, t)		0.0275 (0.0155) [0.0763]		0.0470 (0.0165) [0.0043]
Societal demand (i, t)			0.0171 (0.0122) [0.1586]	-0.0123 (0.0130) [0.3422]
Total firm innovation (i, t)	0.0535 (0.0021) [0.0000]	0.0524 (0.0021) [0.0000]	0.0536 (0.0021) [0.0000]	0.0527 (0.0021) [0.0000]
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	8969	8969	8969	8969

Panel C: Controlling for lagged climate and total firm innovation DV: Climate innovation (i, t+1)				
Model	**(1)**	**(2)**	**(3)**	**(4)**
Climate risk exposure (i, t)	0.0788 (0.0170) [0.0000]	0.0729 (0.0190) [0.0001]	0.0648 (0.0175) [0.0002]	0.0754 (0.0200) [0.0002]
Climate risk exposure (i, t) × Regulatory demand (i, t)		-0.0417 (0.0113) [0.0002]		-0.0476 (0.0112) [0.0000]
Climate risk exposure (i, t) × Societal demand (i, t)			0.0808 (0.0116) [0.0000]	0.0839 (0.0118) [0.0000]
Regulatory demand (i, t)		0.0549 (0.0156) [0.0004]		0.0810 (0.0166) [0.0000]
Societal demand (i, t)			0.0173 (0.0121) [0.1539]	-0.0203 (0.0130) [0.1183]
Climate innovation (i, t)	0.0021 (0.0001) [0.0000]	0.0021 (0.0001) [0.0000]	0.0021 (0.0001) [0.0000]	0.0022 (0.0001) [0.0000]
Total firm innovation (i, t)	0.0283 (0.0025) [0.0000]	0.0269 (0.0025) [0.0000]	0.0279 (0.0025) [0.0000]	0.0264 (0.0026) [0.0000]
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	8969	8969	8969	8969

Note: All regressors are standardized scores; all models include a vector of firm-year controls as specified in the main analysis (control variable coefficient suppressed for brevity); firm-clustered robust standard errors are in parentheses; p values are in brackets.

Climate innovation quality. To strengthen our inferences, we examine the quality of MNEs' climate innovation, since our main analysis captures how climate risks may increase the quantity of climate patents. Specifically, we examine the effect of *climate risk exposure* and the moderation effects of *regulatory* and *societal demand* on the number of citations received by a firm's climate patents aggregated over five or ten years from the date of patent publication. We report the results in Table A6. Consistent with our main analysis, we find a positive and statistically significant effect from *climate risk exposure* on five- and ten-year total *climate patent citations*, a negative and statistically significant interaction between *climate risk exposure* and *regulatory demand*, and a positive and statistically significant interaction between *climate risk exposure* and *societal demand*.

Table A6. Robustness check: MNE climate risk exposure and climate innovation quality

DV	**Climate patent citations (5 year total) (i, t+1)**	**Climate patent citations (10 year total) (i, t+1)**
Model	**(1)**	**(2)**
Climate risk exposure (i, t)	0.0307	0.0328
	(0.0110)	(0.0112)
	[0.0052]	[0.0034]
Climate risk exposure (i, t) × Regulatory demand (i, t)	-0.0894	-0.0603
	(0.0079)	(0.0076)
	[0.0000]	[0.0000]
Climate risk exposure (i, t) × Societal demand (i, t)	0.0734	0.0487
	(0.0063)	(0.0061)
	[0.0000]	[0.0000]
Regulatory demand (i, t)	0.0906	-0.0174
	(0.0113)	(0.0115)
	[0.0000]	[0.1292]
Societal demand (i, t)	-0.1128	0.0873
	(0.0077)	(0.0074)
	[0.0000]	[0.0000]
Total firm innovation (i, t)	0.0558	0.0674
	(0.0013)	(0.0023)
	[0.0000]	[0.0000]
Control	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	7533	6229

Note: All regressors are standardized scores; all models include a vector of firm-year controls as specified in the main analysis (control variable coefficient suppressed for brevity); firm-clustered robust standard errors are in parentheses; p values are in brackets.

Industry heterogeneity. To supplement our main insights, we explore industry heterogeneity. Namely, we examine whether our hypothesized effects might differ across industries with various pollution tendencies and are thus subjecting to different degrees of public scrutiny over corporate

environmental sustainability (i.e., oil & gas industries vs other industries, heavy vs light industries). Relatedly, we examine the potential influences stemming from high vs low industry environmental performance, technological innovation, or competition to uncover whether these industry-level conditions can alter a focal MNE's innovation responses to climate risks, regulatory and societal demands for climate action.

Table A7. Supplemental analysis: Industry heterogeneity

	DV: Climate innovation (i, t+1)				
Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Climate risk exposure (i, t)	0.0461 (0.0200) [0.0215]	0.0213 (0.0204) [0.2973]	0.0665 (0.0203) [0.0010]	0.1828 (0.0287) [0.0000]	0.0373 (0.0226) [0.0984]
Climate risk exposure (i, t) × Oil & gas industries	0.2873 (0.0697) [0.0000]				
Climate risk exposure (i, t) × Heavy industries		0.1869 (0.0189) [0.0000]			
Climate risk exposure (i, t) × High environmental performance industries (j, t)			-0.0753 (0.0171) [0.0000]		
Climate risk exposure (i, t) × High innovation industries (j, t)				-0.1370 (0.0224) [0.0000]	
Climate risk exposure (i, t) × High competition industries (j, t)					-0.0023 (0.0169) [0.8943]
Climate risk exposure (i, t) × Regulatory demand (i, t)	-0.0925 (0.0112) [0.0000]	-0.0948 (0.0118) [0.0000]	-0.0606 (0.0127) [0.0000]	0.0774 (0.0265) [0.0035]	-0.1318 (0.0196) [0.0000]
Climate risk exposure (i, t) × Regulatory demand (i, t) × Oil & gas industries	0.2660 (0.0566) [0.0000]				
Climate risk exposure (i, t) × Regulatory demand (i, t) × Heavy industries		0.0753 (0.0198) [0.0001]			
Climate risk exposure (i, t) × Regulatory demand (i, t) × High environmental performance industries (j, t)			-0.0731 (0.0163) [0.0000]		
Climate risk exposure (i, t) × Regulatory demand (i, t) × High innovation industries (j, t)				-0.1923 (0.0273) [0.0000]	
Climate risk exposure (i, t) × Regulatory demand (i, t) × High competition industries (j, t)					0.0613 (0.0203) [0.0025]

(Table 8 continues)

Climate risk exposure (i, t) × Societal demand (i, t)	0.0860 (0.0119) [0.0000]	0.0673 (0.0134) [0.0000]	0.0423 (0.0145) [0.0035]	0.0279 (0.0224) [0.2143]	0.1276 (0.0217) [0.0000]
Climate risk exposure (i, t) × Societal demand (i, t) × Oil & gas industries	-0.0381 (0.0796) [0.6322]				
Climate risk exposure (i, t) × Societal demand (i, t) × Heavy industries		0.0381 (0.0195) [0.0509]			
Climate risk exposure (i, t) × Societal demand (i, t) × High environmental performance industries (j, t)			0.0796 (0.0141) [0.0000]		
Climate risk exposure (i, t) × Societal demand (i, t) × High innovation industries (j, t)				0.0598 (0.0235) [0.0109]	
Climate risk exposure (i, t) × Societal demand (i, t) × High competition industries (j, t)					-0.0616 (0.0219) [0.0050]
Regulatory demand (i, t)	0.0417 (0.0166) [0.0118]	0.0472 (0.0166) [0.0044]	0.0420 (0.0165) [0.0111]	0.0174 (0.0167) [0.2958]	0.0339 (0.0165) [0.0401]
Societal demand (i, t)	0.0034 (0.0130) [0.7928]	0.0021 (0.0130) [0.8718]	-0.0053 (0.0131) [0.6891]	0.0023 (0.0130) [0.8597]	0.0014 (0.0130) [0.9167]
Control	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	8969	8969	8969	8969	8969

Note: All regressors are standardized scores; all models include a vector of firm-year controls as specified in the main analysis and control for the corresponding industry dummies (control variable coefficient suppressed for brevity); firm-clustered robust standard errors are in parentheses; p values are in brackets.

Model 1 of Table A7 shows the results that compare our hypothesized effects between MNEs in the oil and gas industries and those in the other industries.[4] The positive effect of *climate risk exposure* on *climate innovation* is stronger for MNEs in the oil and gas industries than those in other industries, as suggested by a positive and statistically significant interaction between *climate risk exposure* and the *oil & gas industries* binary indicator. Furthermore, the combined effect between *climate risk exposure* and *regulatory demand* is complementary in the oil and gas industries, as indicated by a positive and statistically significant three-way interaction (i.e., $\beta_{climate\ risk\ exposure \times regulatory\ demand \times oil\ \&\ gas\ industries} = 0.2660$, $p = 0.0000$) larger than the negative two-way interaction (i.e., $\beta_{climate}$

[4] The binary variable, *oil & gas industries*, equals one for MNEs in the oil and gas industries and zero otherwise.

$_{risk\ exposure \times regulatory\ demand}$ = -0.0925, p = 0.0000). In contrast, we do not find the moderation effect associated with *societal demand* to differ between MNEs in the oil and gas industries compared to those in the other industries in our analysis (i.e., Model 1 of Table 8 shows an insignificant three-way interaction between *climate risk exposure*, *societal demand*, and *oil & gas industries*).

Model 2 of Table A7 shows the results that compare our hypothesized effects between MNEs in the heavy industries and those in the other industries (e.g., light industries).[5] The positive effect of *climate risk exposure* on *climate innovation* is stronger for MNEs in heavy industries than those in other industries, as indicated by a positive and statistically significant interaction between *climate risk exposure* and the *heavy industries* binary variable. The substitutive effect associated with *regulatory demand* is weakened for MNEs in the heavy industries, as indicated by a positive and statistically significant three-way interaction (i.e., $\beta_{climate\ risk\ exposure \times regulatory\ demand \times heavy\ industries}$ = 0.0753, p = 0.0000), whereas the complementary effect associated with *societal demand* appears stronger, as suggested by a positive and marginally significant three-way interaction (i.e., $\beta_{climate\ risk\ exposure \times societal\ demand \times heavy\ industries}$ = 0.0381, p = 0.0509).

Model 3 of Table A7 reveals how our hypothesized effects may differ between MNEs in industries with high vs low average environmental performance scores in our sample.[6] The results suggest that MNEs in industries with *higher* levels of environmental performance are *less* sensitive to *climate risk exposure* in terms of developing climate technologies (i.e., interaction between *climate risk exposure* and *high environmental performance industries* is negative and statistically

[5] The binary variable, *heavy industries*, equals one for MNEs in the heavy industries and zero otherwise. Heavy industries include the following: mining (SIC: 10, 12, 13, 14), construction (SIC: 15, 16, 17), lumber and wood product manufacturing (SIC: 24), chemicals and allied product manufacturing (SIC: 28), petroleum refining (SIC: 29), stone, clay, glass, and concrete product manufacturing (SIC: 32), primary metal industries (SIC: 33), industrial and commercial machinery (SIC: 35), and transportation equipment manufacturing (SIC: 37).

[6] The binary variable, *high environmental performance industries*, equals one for MNEs in industries with annual average ASSET4 environmental performance score greater that the industry-year median across our sample and zero otherwise.

significant).[7] Both the negative moderation effect attributed to *regulatory demand* and the positive moderation effect attributed to *societal demand* are stronger for MNEs in industries with higher environmental performance levels.

Models 4 and 5 of Table A7 explore the differences between high vs low innovation industries and high vs low competition industries, respectively.[8] We find that MNEs in high-innovation industries are less sensitive to climate risk in terms of elevating climate innovation, whereas industry competition level does not appear to alter this sensitivity. We also find that the substitutive effect attributed to *regulatory demand* is driven by MNEs in high-innovation or low-competition industries, and that the complementary effect attributed to *societal demand* is driven by MNEs in high-innovation or low-competition industries.[9]

Incremental vs radical climate innovation. In addition, we explore whether our hypothesized effects are driven by MNEs' incremental or radical climate innovation. We use the patent citation network-based *CD score* (Funk & Owen-Smith, 2017) to identify incremental or radical innovation. Specifically, patents with *CD scores* between 0 and 1 are considered radical (or "deviating") as they tend to lead future patents away from the preceding technological development trajectories, whereas those with *CD scores* between -1 and 0 are considered incremental (or

[7] While we do not formally theorize or test the mechanism for this industry heterogeneity pattern, it is plausibly due to shareholder and stakeholder attention to firm climate risk given industry-wide environmental performances: in industries with low average sustainability, shareholders and stakeholders will likely pay heightened attention to the damages of a firm's climate risk exposure (i.e., heightened private monitoring) and urge more proactive firm actions (e.g., climate innovation) to address the risk. We thank an anonymous reviewer for this reasoning.

[8] The binary variable, *high innovation industries*, equals one for MNEs in industries with annual average granted patent count greater that the industry-year median across our sample and zero otherwise. The binary, *high competition industries*, equals one for MNEs in industries with annual HHI of firm sales lower that the industry-year median across our sample and zero otherwise.

[9] Overall, the industry heterogeneity patterns are consistent with a potential moderating role of private monitoring from shareholders and stakeholders on climate issues: in low-sustainability industries, MNEs are likely urged more by shareholders and stakeholders to raise climate innovation to offset climate risk; similarly, heightened private monitoring on sustainability issues in these industries may impose greater urgency to innovate while rendering political lobbying or offshoring less appealing under elevated climate policy pressure, which may explain the weakened substitution between *regulatory demand* and *climate risk exposure* in these industries; concurrently, given elevated *societal demand* on climate actions, heightened private monitoring will likely amplify the MNEs' motivation to capture value creation opportunities via climate innovation not only to offset the costs of climate change on the focal firm but also to develop revenue streams via patent licensing or transferring.

"consolidating") because they tend to direct future patents toward the same trajectories defined by the prior arts (Balachandran & Hernandez, 2018; Funk & Owen-Smith, 2017; Genin et al., 2023).[10] We count the number of incremental or radical climate patents applied by firm *i* in year *t+1* to be the dependent variables.

Table A8. Supplemental analysis: Are the main results driven by MNEs' incremental or radical climate innovation?

Panel A. DV: Incremental climate innovation (i, t+1)				
Model	**(1)**	**(2)**	**(3)**	**(4)**
Climate risk exposure (i, t)	0.1305	0.1077	0.1205	0.1077
	(0.0217)	(0.0237)	(0.0222)	(0.0247)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Climate risk exposure (i, t) × Regulatory demand (i, t)		-0.0549		-0.0627
		(0.0130)		(0.0129)
		[0.0000]		[0.0000]
Climate risk exposure (i, t) × Societal demand (i, t)			0.0653	0.0712
			(0.0142)	(0.0143)
			[0.0000]	[0.0000]
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	8585	8585	8585	8585
Panel B. DV: Radical climate innovation (i, t+1)				
Model	**(1)**	**(2)**	**(3)**	**(4)**
Climate risk exposure (i, t)	0.0193	-0.0531	0.0010	-0.0784
	(0.0315)	(0.0361)	(0.0330)	(0.0388)
	[0.5401]	[0.1417]	[0.9764]	[0.0432]
Climate risk exposure (i, t) × Regulatory demand (i, t)		-0.1518		-0.1572
		(0.0276)		(0.0276)
		[0.0000]		[0.0000]
Climate risk exposure (i, t) × Societal demand (i, t)			0.0799	0.0881
			(0.0228)	(0.0227)
			[0.0005]	[0.0001]
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	6486	6486	6486	6486

Note: An "incremental climate patent" is a Y02 class patent with a negative or zero *CD score*, and a "racial climate patent" is a Y02 class patent with a positive *CD score*. All regressors are standardized scores; all models include a vector of firm-year controls as specified in the main analysis and control for the corresponding moderators (control variable coefficient suppressed for brevity); firm-clustered robust standard errors are in parentheses; p values are in brackets.

[10] We note that both incremental and radical innovation will require substantive firm investment in R&D; the two differ in their value creation and early-stage R&D risks: radical innovation emphasizes scientific value (e.g., re-directing future technological trajectories and potentially paradigm-shifting), which is often risky at the early stage since more exploration is required; incremental innovation emphasizes practical value (e.g., reinforcing existing technological development and thus focusing on practical solutions for existing problems) and often calls for a more defined R&D approach with lower early-stage risks.

Table A8 shows the effects of *climate risk exposure*, *regulatory* and *societal demand* on MNEs' *incremental climate innovation* (Panel A) or *radial climate innovation* (Panel B). The results in Panel A are consistent with the main results reported in Table 3. While we do not find consistent patterns regarding how *climate risk exposure* alone would affect MNEs' radical climate innovation, the moderation effects attributed to *regulatory* and *societal demand* remain consistent with our main results (Table A8: Panel B). The full model (Model 5) in Panel B indicates that *climate risk exposure* will raise *radical climate innovation* only when a focal MNE faces both low *regulatory demand* and high *societal demand*.

These supplemental results indicate that our hypothesized effects are driven by MNEs' incremental climate innovation development. This suggests that MNEs take a pragmatic R&D approach to address the climate challenge since incremental innovation often yields greater predictability and more timely solutions to current problems. However, MNEs may also devote R&D resources toward radical technology development in response to climate risk when other formal and informal institutional conditions are conducive (i.e., less stringent regulatory pressure and more urgent societal needs for climate action).

Home vs host country institutions. Finally, in Table A9, we show how home and host institutional conditions—namely, *home (host) country regulatory* and *societal demands* for climate action—compare in terms of their moderation effects on the quantity and quality of MNE climate innovation. We find that *home* and *host country regulatory* and *societal demands* exert comparable moderation effects on the quantity of MNE climate innovation (Models 1 and 2). Regarding the quality of MNE climate innovation, we find that *home country regulatory demand* exerts a larger substitutive effect than *host country regulatory demand* does (Models 3 and 5), and that *host country societal demand* exerts a larger complementary effect than *home country societal demand* does (Models 4 and 6). That is, MNEs appear to be swayed more strongly by formal institutions at home

and informal institutions abroad regarding their innovation responses to global climate risk as far as innovation quality is concerned.[11]

Table A9. Supplemental analysis: Comparing the contingency effects of regulatory or societal demands between home and host countries

DV	Climate innovation (i, t+1)		Climate patent citations (5 year total) (i, t+1)		Climate patent citations (10 year total) (i, t+1)	
Model	(1)	(2)	(3)	(4)	(5)	(6)
Climate risk exposure (i, t)	0.0480	0.0402	-0.0088	0.0351	0.2905	0.1444
	(0.0310)	(0.0190)	(0.0181)	(0.0102)	(0.0170)	(0.0104)
	[0.1219]	[0.0343]	[0.6261]	[0.0006]	[0.0000]	[0.0000]
Climate risk exposure (i, t) × Home country regulatory demand (i, t)	-0.0800		-0.2103		-0.2393	
	(0.0251)		(0.0194)		(0.0220)	
	[0.0014]		[0.0000]		[0.0000]	
Climate risk exposure (i, t) × Host country regulatory demand (i, t)	-0.0984		-0.1499		-0.1314	
	(0.0271)		(0.0204)		(0.0228)	
	[0.0003]		[0.0000]		[0.0000]	
Climate risk exposure (i, t) × Home country societal demand (i, t)		0.1767		0.0754		0.2153
		(0.0339)		(0.0186)		(0.0186)
		[0.0000]		[0.0001]		[0.0000]
Climate risk exposure (i, t) × Host country societal demand (i, t)		0.1702		0.1409		0.2899
		(0.0328)		(0.0182)		(0.0180)
		[0.0000]		[0.0000]		[0.0000]
Control	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7963	8847	6688	7433	5534	6185

Note: All regressors are standardized scores; all models include firm-year control variables as specified in the main analysis and control for the contingency variables and lagged firm innovation (control variable coefficient suppressed for brevity); firm-clustered robust standard errors are in parentheses; p values are in brackets.

[11] We note that several regressors in Table A9 have high pairwise correlations (see Table 2): *home country regulatory demand*, *host country regulatory demand*, *home country societal demand*, and *host country societal demand* are strongly correlated with *climate risk exposure*. Therefore, the lack of statistical significance of the estimated impact of *climate risk exposure* in Model 1 and Model 3 should be interpreted with caution, since multicollinearity could reduce the statistical power in these models.