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Complex technologies and speed of diffusion in Europe: Evidence from green patents

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SPES Sustainability performances, evidence & scenarios

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Background

Diffusion of Green Technologies

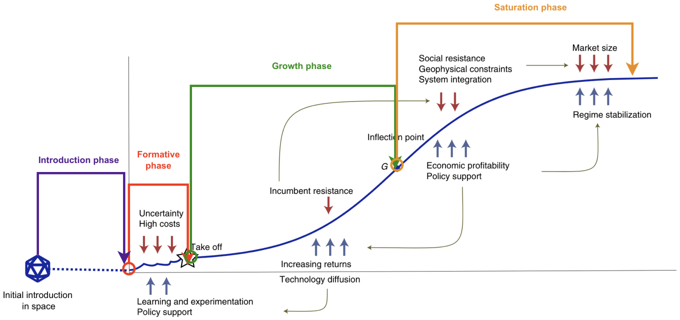
- Unprecedented challenges related to climate change.
- Accelerating the diffusion of Green Technologies (GTs) to mitigate GHG emissions (OECD, 2009; Hasna et al., 2023), yet multiple barriers (e.g., Rennings, 2000; Ghisetti and Quatraro, 2017).
- Tech. complexity may represent a barrier.
- GTs are more complex than conventional techs $\Rightarrow$ require recombining numerous, distant, and cognitively diverse knowledge domains (Barbieri et al., 2016; Fusillo, 2019); tech. complexity increases over time (Broekel, 2019).
- Most widely validated complexity framework:
  Economic Complexity (EC) $\Rightarrow$ Captures how well a location combines diverse capabilities to generate unique and complex technologies (Hidalgo and Hausmann, 2009; Tacchella et al., 2012).

Complexity & Diffusion

- The spatial dimension of the tech. diffusion-complexity relationship has been investigated...
  1. Concentration in productive places (e.g., Pintar and Scherngell, 2022; Mewes and Broekel, 2022), with European regions as illustrative cases (Antonelli, 2022; Pinheiro et al., 2022).
  2. Larger knowledge spillovers (e.g., Dechezlepretre et al., 2017; Barbieri et al., 2020).
- ... But the temporal dimension remains largely unexplored.

Complexity & Diffusion

- The temporality of tech. diffusion can be investigated in two ways:
  1. **Introduction phase** ⇒ from global emergence to locational introduction (Li et al., 2021, 2023).
  2. **Trajectory phases** ⇒ from locational introduction to key milestones along the trajectory curve: take-off, inflection, and saturation (Andersen, 1999; Bento et al., 2018; Cherp et al., 2021).
- Recent evidence shows a longer time to take-off for complex novel techs (Pezzoni et al., 2022).



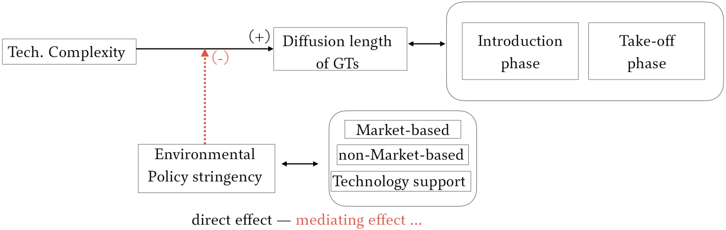
Motivations & Hypotheses

Motivation

- Does complexity $\Rightarrow$ greater sustainability? Consensus is lacking, but several encouraging empirical findings:
  1. Economically (e.g., Hidalgo and Hausmann, 2009; Mewes and Broekel, 2022)
  2. Socially (e.g., Hartmann et al., 2017; Sbardella et al., 2017)
  3. Environmentally (e.g., Mealy and Teytelboym, 2022; Romero and Gramkow, 2021)
- Limited research addresses the temporality of GTs diffusion and its connection to complexity, despite existing research perspectives.
- The complexity paradigm holds potential for understanding challenges in accelerating GTs diffusion.

Research Question & Hypotheses

- One of the key questions is: To what extent does technological complexity impact the diffusion of GTs across European countries?
- Dependent variables: length of (1) the introduction phase, and (2) the formative phase (up to take-off).
- Independent variables: technological complexity, and environmental policy stringency.
- Hypothesis 1: **Technological complexity (+)** associated with the length of the diffusion of GTs.
- Hypothesis 2: **National environmental policy stringency (-)** mitigates the (+) effect of technological complexity on the length of the diffusion of GTs.



Methodology

Patent data

- Patents reliably measure GTs (Barbieri et al., 2016).
- Unit of analysis: **Country/GT pair** (EU-27, the UK, Norway and Switzerland; 43 GTs)

  Patent selection ⇒ DOCDB Patent family (PATSTAT):

  1. Contains at least one application's CPC code aligned to a **Green class** (i.e., within **Y02 or Y04S**) (see Veefkind et al., 2012).
  2. Filed at the European Patent Office (ensures patent quality & homogeneity).
  3. Priority date between 1979-2017 (before truncation).
  4. Country identified by inventor's address (full counting).

- Technology:
  - At the six-digit level; e.g., 'Y02B20' corresponds to energy-efficient lighting.
  - Minimum of 500 patents per tech. globally (between 1979 and 2017) ⇒ 43 GTs retained.

Complexity Measure (1)

- **Complexity-Fitness Method (CFM)** (Tacchella et al., 2012) is a widely adopted and robust measure of EC (e.g., Cristelli et al., 2013; de Cunzo et al., 2022; Sbardella et al., 2018; Napolitano et al., 2022).
- **Complexity** is measured using an RTA matrix on global patent data ($M_{c,k,t}$), capturing national (c) specialization in technology (k).

$$RTA_{c,k,t} = \frac{PO_{c,k,t} / \sum_k PO_{c,k,t}}{\sum_c PO_{c,k,t} / \sum_{c,k} PO_{c,k,t}} \qquad M_{c,k,t} = \begin{cases} 0 & \text{if } RTA_{c,k,t} \leq 1 \\ 1 & \text{if } RTA_{c,k,t} > 1 \end{cases}$$

- $M_{c,k,t}$ = 0/1: no specialization/specialization in a technology field given the global technological landscape.
- Binary RTA is preferred, continuous values tend to be unstable and noisy (e.g., Balland et al., 2019).

Complexity Measure (2)

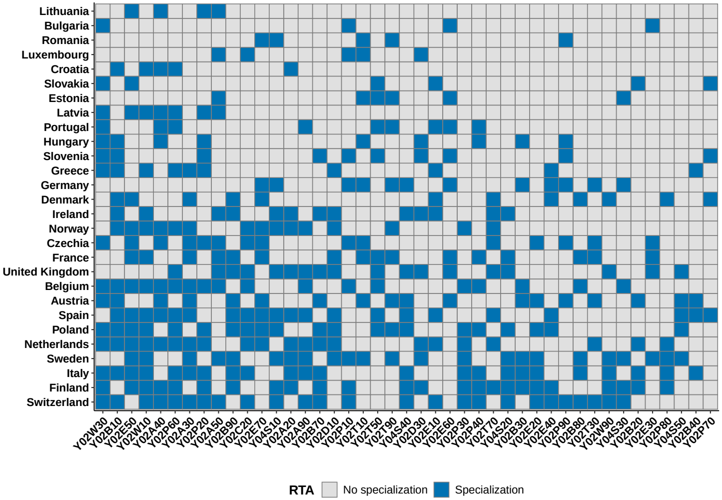


Figure 1: Matrix example using RTA, selection of European countries and GTs

(EPO patents, 2015-2017 averaged window)

Complexity Measure (3)

- **National fitness (F_c)** and **technology sophistication (Q_k)** are iteratively computed and updated using the following equations (Tacchella et al., 2012):

$$Q_{k,t}^{0} = 1, \quad F_{c,t}^{0} = 1 \quad \forall\, k \in K,\, c \in C$$

$$\begin{cases} \tilde{F}_{c,t}^{n} = \displaystyle\sum_{k=1}^{K} M_{c,k} Q_{k,t}^{(n-1)} \\ \tilde{Q}_{k,t}^{n} = \left(\dfrac{1}{\sum_{c=1}^{R} M_{c,k} \left(\frac{1}{F_{c,t}^{n-1}} \right)} \right) \end{cases} \qquad \begin{cases} F_{c,t}^{n} = \dfrac{\tilde{F}_{c,t}^{n}}{\langle \tilde{F}_{c,t}^{n} \rangle} \\ Q_{k,t}^{n} = \dfrac{\tilde{Q}_{k,t}^{n}}{\langle \tilde{Q}_{k,t}^{n} \rangle} \end{cases}$$

- A high national fitness ($F_{c,t}$) indicates specialization in diverse and sophisticated technologies ($Q_{k,t}$), while higher technology sophistication ($Q_{k,t}$) reflects that only a few countries specialize in this technology, and those countries have relatively high fitness ($F_{c,t}$).

Complexity Measure (4)

- Two adaptations to measure complexity per country-GT pair over time:

  1. **Relative complexity measure:**

     $$\text{Fitness-Complexity}_{k,i,t} = Q_{k,t} - F_{i,t}$$

     How complex is a GT compared to the country's average technological capabilities?

  2. **Inverted ranking transformation** (due to independent matrix computation) (e.g., Caldarola et al., 2024)

     A higher-ranked GT-European country pair reflects a greater complexity gap between the GT and the country's average technological capabilities compared to other pairs.

Diffusion Measure (1): Introduction phase

- Diffusion in terms of **technological knowledge** (via patents).
- A country **introduced a GT** as of its **earliest priority date**.
  1. **Global introduction period: 1979–2017** → Marks the global emergence of green patents.
  2. **European introduction period: 1995-2017** → Aligns with the start of available data on national environmental policy stringency.

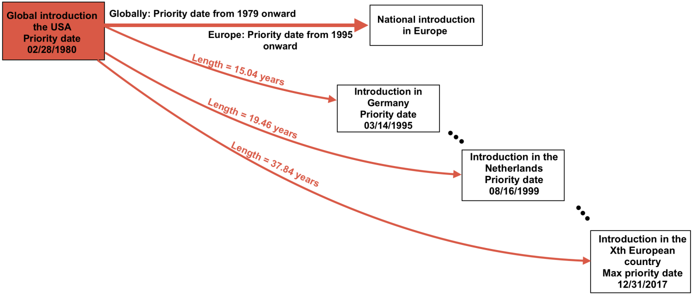


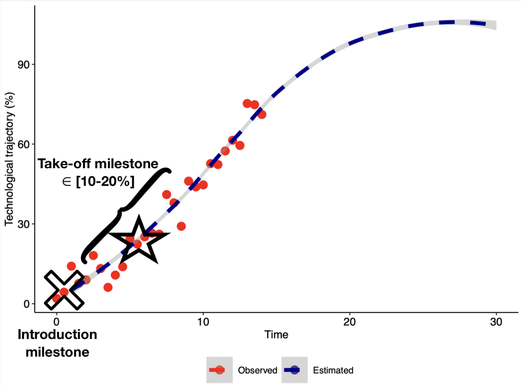
Figure 2: Illustrative example of the introduction phase - Reducing energy consumption technologies in ICT (CPC: Y02D30)

Diffusion Measure (2): Take-off phase

- Capturing the take-off milestone requires identifying tech. trajectories.
- Trajectory is **measured by the cumulative count of patents** over time for each GT, starting from its national introduction.
- Similar measures exist (e.g., Verhoeven et al., 2016; Pezzoni et al., 2022, 2023), but without associating trajectories to specific country–technology pairs. E.g., the unit France/Y02T10 corresponds to the French green transport.
- Two main challenges:
  1. Identifying distinct trajectory phases (i.e., formative, growth, and saturation phases).
  2. Risk of underestimating take-off for emerging GTs.

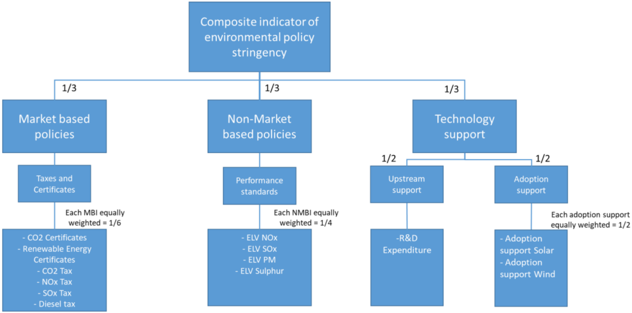
Diffusion Measure (3): Take-off phase

- A **logistic function** fits the trajectory to its asymptotic limit—a widely accepted S-shape in the diffusion literature (e.g., Cherp et al., 2021; Andersen, 1999) (for evaluation of the fitting, click here).
- **Take-off milestone** corresponds to **10% of trajectory's maturity** (e.g., Pezzoni et al., 2022).



Environmental Policy Stringency Measure (1)

- The OECD's **Environmental Policy Stringency (EPS**) index is defined *"as a higher, explicit or implicit, cost of polluting or environmentally harmful behavior"* (Botta and Koźluk, 2014; Kruse et al., 2022).
- EPS index is a widely used measure (Galeotti et al., 2020), it ranges from 0 (not stringent) to 6 (most stringent), is measured annually, and is **disaggregated into market-based, non-market-based, and technology support instruments**.



Note: The figure shows the aggregation structure of the revised EPS index (referred to as "EPS21").
Source: OECD.

Environmental Policy Stringency Measure (2)

- **A relative EPS index** is used instead of raw stringency to reflect each European country's position within the European context.

  (for visualization of the differences, click here)

- Relative EPS index is defined as:

$$\text{Relative EPS}_{c,t,k} = \frac{\text{EPS}_{c,t,k}}{\frac{1}{N}\sum_{j\neq c}\text{EPS}_{j,t,k}} \quad \text{for all } j \text{ where } j \neq c$$

- **Leader and laggard countries** are identified via yearly dummies by instrument type:

$$\text{Dummy EPS}_{c,t,k} = \begin{cases} 1 & \text{if Relative EPS}_{c,t,k} > \lambda\ \text{EPS}_{\text{Europe}-c,t,k} \\ 0 & \text{if Relative EPS}_{c,t,k} \leq \lambda\ \text{EPS}_{\text{Europe}-c,t,k} \end{cases}$$

- Where λ **is a threshold**, taking two main values:
  1. **The average of other European countries**,
  2. **The 90th percentile of the European distribution** (with $\neq$ thresholds tested).

- To ensure stability, a value of one is assigned only if the condition is met in the two prior years, for a given country and instrument type.

Econometric estimates

- **Introduction phase** (cross-sectional data): Natural logarithm of the time lag (in days) between global and national introduction of GTs $\Rightarrow$ OLS estimation with time fixed effects:

$$\begin{aligned}\text{Log[Y]}_{i,c}^{introduction} &= \alpha + \beta_0 + \theta_1 \text{Log[Rank(Complexity)]}_{c,i,t-1} \\ &+ \beta_1 (\text{EPS} > \lambda \text{European-EPS})_c (t-s) + \beta_2 Z_c + \\ &\beta_3 X_c (t-1) + \sum_p \beta_{4+p} \text{Period}_p + \epsilon_{i,c}\end{aligned}$$

- **Take-off phase** (longitudinal data): Percentage of estimated trajectory maturity from national introduction of GTs to national take-off $\Rightarrow$ panel fixed effects estimation:

$$\begin{aligned}\text{Y}_{i,c}(t)^{take-off} &= \alpha + \beta_0 + \theta_1 \text{Log[Rank(Complexity)]}_{c,i,t-1} \\ &+ \beta_1 (\text{EPS} > \lambda \text{European-EPS})_c (t-s) + \beta_2 X_c (t-1) \\ &+ \sum_t \beta_{3+t} \text{year}_{i,c,t} + \gamma_i + \delta_c + \epsilon_{i,c}\end{aligned}$$

Where:

$$\text{Y}_{i,c}(t)^{take-off} = \left[\frac{\text{Maturity estimated}_{i,c}(t)}{\text{Maturity estimated}_{i,c}^{\text{Take-Off}}} \right] \times 100$$

Descriptive statistics

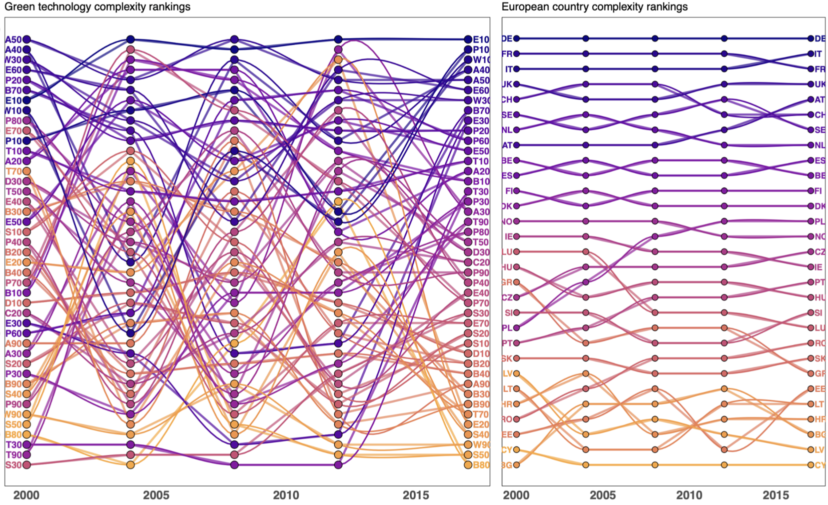


Figure 3: Comparison of GT and European country complexity rankings over time (2000-2017)

Note: Colors correspond to the ranking in 2017 (darker tones indicating higher complexity)

Descriptive statistics

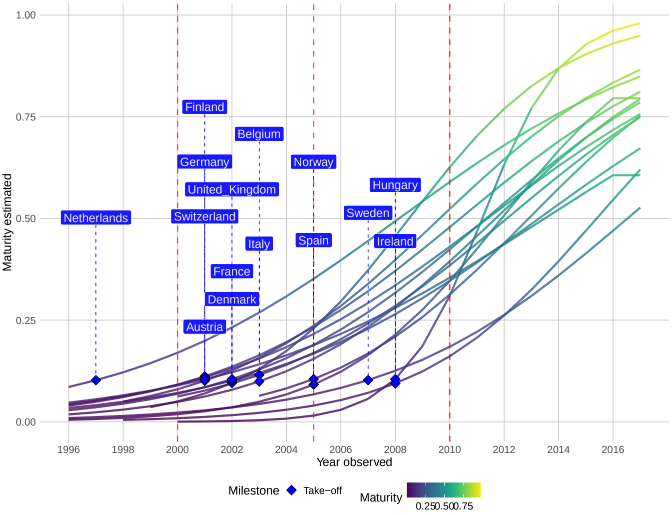


Figure 4: Estimated European trajectories for reducing energy consumption technologies in ICT (Logistic function fitted on CPC: Y02D30; take-off defined at 10% of estimated maturity)

Results - Introduction phase

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	Dependent variable: log of time between global and national GT introduction				
	(1)	(2)	(3)	(4)	(5)
$\text{Log[Rank(Complexity)]}_{c,i,t-1}$	0.033^{***}	0.026^{***}	0.023^{***}	0.024^{***}	0.017^{***}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$\text{Log[GDP per capita]}_{c,t-1}$		-0.017	-0.014	-0.014	0.0002
		(0.012)	(0.011)	(0.011)	(0.006)
$\text{Log[Trade Openness]}_{c,t-1}$		0.030^{***}	0.031^{***}	0.031^{***}	0.030^{***}
		(0.011)	(0.011)	(0.011)	(0.010)
$\text{Pioneer}_{c,i}$			-0.027^{***}	-0.027^{**}	-0.025^{***}
			(0.010)	(0.011)	(0.009)
$\text{Border}_{c,i}$			-0.016^{**}	-0.016^{**}	-0.014^{**}
			(0.008)	(0.008)	(0.007)
$\text{Firms count}_{c,i,t-1}$				0.0004	-0.0003
				(0.002)	(0.002)
$\text{Universities count}_{c,i,t-1}$				0.009	0.009
				(0.011)	(0.012)
$\text{Log[Green diversification +1]}_{c,t-1}$					-0.017^{**}
					(0.008)
Time FE	✓	✓	✓	✓	✓
Observations	1,048	1,048	1,048	1,048	1,048
Adjusted R^2	0.922	0.925	0.925	0.925	0.926

Note: SE are heteroskedasticity-robust and clustered at the country level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

- A one-percent increase in the complexity rank corresponds to a 1.7% increase in the time lag for introducing GTs.

Results - Introduction phase

	Dependent variable: log of time between global and national GT introduction									
	Above European average stringency					Strong sringency in Europe (90^{th} *percentile*)				
	EPS t-5	**EPS t-4**	**EPS t-3**	**EPS t-2**	**EPS t-1**	**EPS t-5**	**EPS t-4**	**EPS t-3**	**EPS t-2**	**EPS t-1**
$\text{Log[Rank(Complexity)]}_{c,i,t-1} \times$ MBPc,t $> \mu\text{MBP}_{Europe-c,t}$	0.0001	-0.002	-0.021	-0.022	-0.026^{**}					
	(0.030)	(0.018)	(0.013)	(0.016)	(0.010)					
$\text{Log[Rank(Complexity)]}_{c,i,t-1} \times$ MBPc,t $> P_{90}(\text{MBP}_{Europe-c,t})$						-0.067^{***}	-0.070^{***}	-0.121^{***}	-0.083^{***}	-0.056^{***}
						(0.014)	(0.013)	(0.027)	(0.019)	(0.016)
$\text{Log[Rank(Complexity)]}_{c,i,t-1} \times$ NMBPc,t $> \mu\text{NMBP}_{Europe-c,t}$	-0.069^{***}	-0.023	0.002	-0.018	-0.021^{*}					
	(0.023)	(0.020)	(0.010)	(0.016)	(0.012)					
$\text{Log[Rank(Complexity)]}_{c,i,t-1} \times$ NMBPc,t $> P_{90}(\text{NMBP}_{Europe-c,t})$						-0.008	0.025	-0.023^{***}	-0.025^{***}	-0.026^{***}
						(0.030)	(0.050)	(0.007)	(0.006)	(0.006)
$\text{Log[Rank(Complexity)]}_{c,i,t-1} \times$ TSc,t $> \mu\text{TS}_{Europe-c,t}$	0.013	-0.004	0.020	-0.003	0.002					
	(0.027)	(0.018)	(0.015)	(0.013)	(0.011)					
$\text{Log[Rank(Complexity)]}_{c,i,t-1} \times$ TSc,t $> P_{90}(\text{TS}_{Europe-c,t})$						-0.042^{***}	-0.021	0.015	0.018	0.037^{**}
						(0.014)	(0.018)	(0.011)	(0.011)	(0.016)
$\text{Log[Rank(Complexity)]}_{c,i,t-1}$	0.018^{***}	0.017^{**}	0.011	0.031^{***}	0.030^{***}	0.016^{***}	0.016^{**}	0.031^{***}	0.031^{***}	0.030^{***}
	(0.007)	(0.007)	(0.010)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
MBPc,t $> \mu\text{MBP}_{Europe-c,t}$	0.009	0.020	0.129	0.122	0.155^{**}					
	(0.189)	(0.118)	(0.083)	(0.106)	(0.061)					
MBPc,t $> P_{90}(\text{MBP}_{Europe-c,t})_{c,t}$						0.424^{***}	0.446^{***}	0.716^{***}	0.457^{***}	0.321^{***}
						(0.091)	(0.083)	(0.164)	(0.116)	(0.105)
NMBPc,t $> \mu\text{NMBP}_{Europe-c,t}$	0.482^{***}	0.169	-0.033	0.115	0.138^{*}					
	(0.148)	(0.132)	(0.065)	(0.102)	(0.072)					
NMBPc,t $> P_{90}(\text{NMBP}_{Europe-c,t})$						0.138	-0.087	0.128^{***}	0.132^{***}	0.135^{***}
						(0.177)	(0.301)	(0.038)	(0.032)	(0.033)
TSc,t $> \mu\text{TS}_{Europe-c,t}$	-0.071	0.041	-0.136	-0.007	-0.032					
	(0.173)	(0.112)	(0.089)	(0.082)	(0.067)					
TSc,t $> P_{90}(\text{TS}_{Europe-c,t})$						0.309^{***}	0.155	-0.094	-0.096	-0.187^{**}
						(0.083)	(0.107)	(0.060)	(0.062)	(0.081)
Control variables	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	908	908	908	908	908	908	908	908	908	908
Adjusted R^2	0.916	0.913	0.911	0.912	0.910	0.915	0.913	0.912	0.911	0.911

Note: SE are heteroskedasticity-robust and clustered at the country level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

- E.g., a one-percent increase in the complexity rank, combined with market-based environmental policy stringency that is (1) above the European average or (2) in the top 10% of European leaders, is associated with a 2.6% and 5.6% reduction, respectively, in the time lag for introducing GTs.

Results - Take-off phase

Results - Take-off phase

	Dependent variable: percentage of trajectory maturity estimated until take-off (10%)				
	(1)	(2)	(3)	(4)	(5)
Log[Rank(Complexity)]$_{c,i,t-1}$	-2.668	-3.203^{***}	-3.550^{***}	-3.505^{***}	-2.167^{***}
	(1.994)	(1.243)	(1.247)	(1.240)	(0.826)
GDP per capita$_{c,t-1}$		0.006^{***}	0.006^{***}	0.006^{***}	-0.0003
		(0.001)	(0.0005)	(0.0005)	(0.0002)
RTA$_{c,t-1}$		0.052	-0.981^{*}	-0.976^{*}	0.722^{**}
		(0.410)	(0.556)	(0.565)	(0.283)
Trade Openness$_{c,t-1}$		0.622^{***}	0.606^{***}	0.604^{***}	0.087^{***}
		(0.157)	(0.158)	(0.158)	(0.026)
Firms count$_{c,i,t-1}$			1.383^{***}	1.382^{***}	0.623^{***}
			(0.274)	(0.275)	(0.124)
Universities count$_{c,i,t-1}$			2.414^{***}	2.434^{***}	0.307
			(0.502)	(0.504)	(0.279)
Green diversification$_{c,t-1}$				0.151	0.096
				(0.163)	(0.094)
Country FE	✓	✓	✓	✓	✓
Technology FE	✓	✓	✓	✓	✓
Year FE	×	×	×	×	✓
Observations	3,349	3,349	3,349	3,349	3,349
Adjusted R^2	0.146	0.763	0.770	0.770	0.897

Note: SE are Driscoll-Kraay robust. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

- A one-percent increase in the complexity rank is associated with a 2.17% decrease in the trajectory maturity needed for GTs to take off.

Results - Take-off phase

	Dependent variable: percentage of trajectory maturity estimated until take-off (10%)									
	Above European average stringency					Strong sringency in Europe (90^{th} percentile)				
	EPS t-5	**EPS t-4**	**EPS t-3**	**EPS t-2**	**EPS t-1**	**EPS t-5**	**EPS t-4**	**EPS t-3**	**EPS t-2**	**EPS t-1**
Log[Rank(Complexity)]$_{c,i,t-1}\times$ MBPc,t $>$ μMBPEurope-c,t	1.925**	0.954	−0.065	−0.261	−0.586					
	(0.785)	(0.932)	(0.802)	(0.996)	(1.012)					
Log[Rank(Complexity)]$_{c,i,t-1}\times$ MBPc,t $>$ P_{90}(MBPEurope-c,t)						11.627***	10.947***	10.614***	9.297***	5.223*
						(2.273)	(1.957)	(3.008)	(3.508)	(3.109)
Log[Rank(Complexity)]$_{c,i,t-1}\times$ NMBPc,t $>$ μNMBPEurope-c,t	0.074	0.487	1.334	4.717***	4.514**					
	(0.453)	(0.441)	(1.351)	(1.809)	(1.795)					
Log[Rank(Complexity)]$_{c,i,t-1}\times$ NMBPc,t $>$ P_{90}(NMBPEurope-c,t)						1.459	2.480***	3.681***	3.474***	3.164***
						(0.969)	(0.883)	(0.614)	(0.687)	(0.768)
Log[Rank(Complexity)]$_{c,i,t-1}\times$ TSc,t $>$ μTSEurope-c,t	−0.016	0.679	0.084	0.040	0.027					
	(0.671)	(0.785)	(0.552)	(0.255)	(0.467)					
Log[Rank(Complexity)]$_{c,i,t-1}\times$ TSc,t $>$ P_{90}(TSEurope-c,t)						2.897	3.297	3.292**	1.517	1.976
						(2.923)	(2.699)	(1.512)	(1.749)	(1.405)
Log[Rank(Complexity)]$_{c,i,t-1}$	−2.653***	−2.976***	−2.960**	−4.947***	−4.866***	−3.059***	−3.133***	−4.065***	−3.958***	−3.637***
	(0.755)	(0.770)	(1.210)	(1.569)	(1.779)	(0.746)	(0.677)	(0.933)	(1.038)	(1.085)
MBPc,t $>$ μMBPEurope-c,t	−9.359**	−4.654	0.588	1.718	4.505	−61.976***	−58.804***	−58.425***	−53.335***	−32.054*
	(4.370)	(4.850)	(4.240)	(5.373)	(5.391)	(12.503)	(10.866)	(16.954)	(20.700)	(18.956)
MBPc,t $>$ P_{90}(MBPEurope-c,t)						11.627***	10.947***	10.614***	9.297***	5.223*
						(2.273)	(1.957)	(3.008)	(3.508)	(3.109)
NMBPc,t $>$ μNMBPEurope-c,t	0.850	−1.517	−6.734	−28.171***	−26.300***	−5.783	−10.599***	−15.688***	−15.938***	−15.442***
	(2.461)	(2.487)	(7.685)	(10.262)	(9.733)	(4.446)	(4.053)	(3.620)	(3.230)	(3.275)
NMBPc,t $>$ P_{90}(NMBPEurope-c,t)						1.459	2.480***	3.681***	3.474***	3.164***
						(0.969)	(0.883)	(0.614)	(0.687)	(0.768)
TSc,t $>$ μTSEurope-c,t	−0.903	−5.168	−2.217	−1.344	−0.193	−16.056	−19.489	−21.205	−10.120	−11.768
	(3.845)	(3.955)	(2.388)	(1.234)	(2.167)	(15.103)	(14.339)	(7.803)	(9.848)	(7.819)
TSc,t $>$ P_{90}(TSEurope-c,t)						2.897	3.297	3.292**	1.517	1.976
						(2.923)	(2.699)	(1.512)	(1.749)	(1.405)
Control variables	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Technology FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3,349	3,349	3,349	3,349	3,349	3,349	3,349	3,349	3,349	3,349
Adjusted R^2	0.897	0.897	0.897	0.898	0.898	0.898	0.899	0.899	0.898	0.898

Note: SE are Driscoll-Kraay robust. *p$<$0.1; **p$<$0.05; ***p$<$0.01

- E.g., a one-percent increase in the complexity rank, combined with non-market-based environmental policy stringency that is (1) above the European average or (2) in the top 10% of European leaders, is associated with a 4.51% and 3.16% increase, respectively, in the trajectory maturity needed for GTs to take off.

Conclusion / Perspectives

Conclusion / & Perspectives

- **Conclusions based on the results**
    1. Technological complexity—when accounting for national capabilities—hinders both the introduction and take-off phases of GTs diffusion in European countries.
    2. Highly stringent domestic environmental regulation—particularly through market-based instruments—mitigates the hindering effect of complexity on national diffusion.
    3. This mitigation effect is weaker when using overly strict non-market-based instruments during the take-off phase.
- **Robustness checks**
    1. Alternative measures of tech. complexity: the original Method of Reflections (Hidalgo and Hausmann, 2009) and the Method of Structural Diversity (Broekel, 2019).
    2. Alternatives raw measures, and different thresholds for environmental policy stringency (15^{th} and 20^{th} percentiles).
    3. Alternative take-off thresholds: not only the estimated but also the observed alternatives (12%, 15%, 17% and 20%).

Conclusion / & Perspectives

- **Perspectives/Open questions**

    1. How to better examine **the long-term effects of environmental policy stringency?** Simply using separate regressions with different lags may not suffice. Including the lags simultaneously could lead to multicolinearity. Any suggestion?
    2. Investigate the role of additional policy dimensions, especially **the sequencing and interaction of policies**, which are known to produce synergistic, counterproductive, or additive effects, and may further support the diffusion of GTs (e.g. Boonekamp, 2006; Wiese et al., 2018; Howlett, 2019).
    3. Patents capture an early stage of the TLC, prior to commercialization and widespread adoption $\rightarrow$ Linking GTs to green products or trademarks (e.g., using cross-relatedness methods) (e.g. Castaldi and Drivas, 2023; de Cunzo et al., 2022) may help **identify adoption take-off**.

Thank you!

Appendices

Tech. Trajectory Measure

- Logistic estimation is performed using the Levenberg-Marquardt Algorithm (e.g., Cherp et al., 2021), implementing the following function:

$$f(t) = \frac{L}{1 + e^{-k\cdot(t-t_0)}} \tag{1}$$

- L is saturation level, k is steepness at the inflection, and t_0 is the fractional year estimated at the inflection.
- Take-off is defined as a linear combination of k and t_0, and corresponds to 10% of saturation level (e.g., Pezzoni et al., 2022).

$$t_{10\%} = t_0 - \frac{2.2}{k} \tag{2}$$

- Evaluating the fit:
  1. Trajectories $\geq$ 20 obs. & $R^2 \geq 90\%$ (Andersen, 1999; Pezzoni et al., 2022)
  2. Maturity for the first observed year below the take-off milestone ($< 10\%$)
  3. Maturity for the last observed year above the inflection milestone ($\geq 50\%$) (as Logistic function is symmetric before/after inflection)
  4. Trajectories with take-off $\in [1995, 2017]$ (limit of observation period)

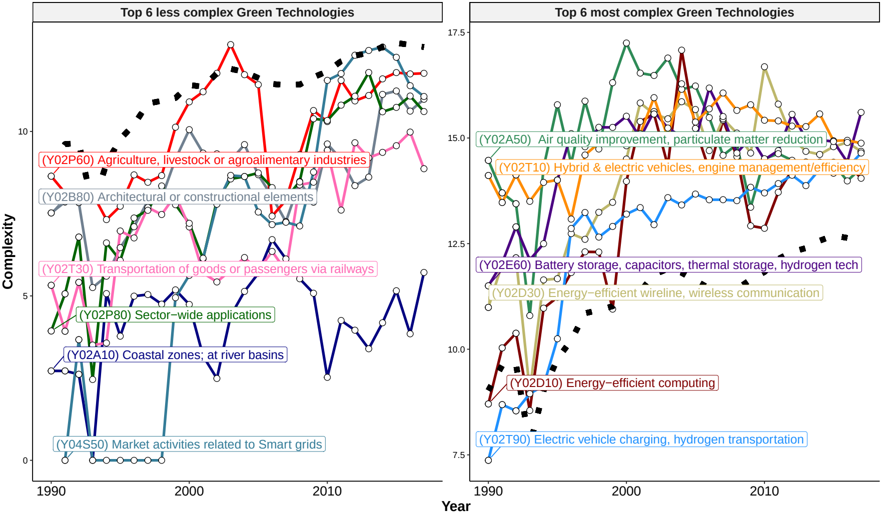
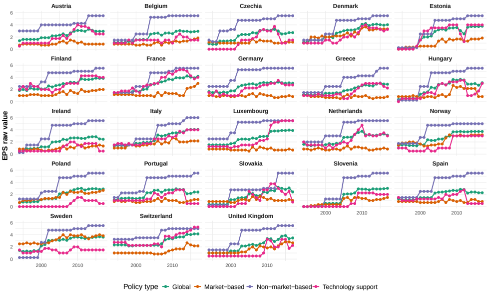
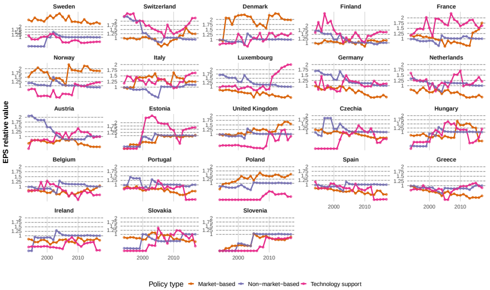


Figure 5: Top and bottom green technologies by complexity (1990 to 2017)

Note: The black dotted line represents the average complexity of GTs.

Raw vs. Relative EPS





(original slide, click here)

Results - Introduction phase

	Dependent variable: log of time between global and national GT introduction									
	Above European average stringency					Strong sringency in Europe				
	EPS t-5	**EPS t-4**	**EPS t-3**	**EPS t-2**	**EPS t-1**	**EPS t-5**	**EPS t-4**	**EPS t-3**	**EPS t-2**	**EPS t-1**
Log[Rank(Complexity)]$_{c,i,t-1}\times$ MBPc,t $> \mu$MBP$_{Europe-c,t}$	0.0001	-0.002	-0.021	-0.022	-0.026^{**}					
	(0.030)	(0.018)	(0.013)	(0.016)	(0.010)					
Log[Rank(Complexity)]$_{c,i,t-1}\times$ MBPc,t $> P_{90}$(MBP$_{Europe-c,t}$)						-0.067^{***}	-0.070^{***}	-0.121^{***}	-0.083^{***}	-0.056^{***}
						(0.014)	(0.013)	(0.027)	(0.019)	(0.016)
Log[Rank(Complexity)]$_{c,i,t-1}\times$ NMBPc,t $> \mu$NMBP$_{Europe-c,t}$	-0.069^{***}	-0.023	0.002	-0.018	-0.021^{*}					
	(0.023)	(0.020)	(0.010)	(0.016)	(0.012)					
Log[Rank(Complexity)]$_{c,i,t-1}\times$ NMBPc,t $> P_{90}$(NMBP$_{Europe-c,t}$)						-0.008	0.025	-0.023^{***}	-0.025^{***}	-0.026^{***}
						(0.030)	(0.050)	(0.007)	(0.006)	(0.006)
Log[Rank(Complexity)]$_{c,i,t-1}\times$ TSc,t $> \mu$TS$_{Europe-c,t}$	0.013	-0.004	0.020	-0.003	0.002					
	(0.027)	(0.018)	(0.015)	(0.013)	(0.011)					
Log[Rank(Complexity)]$_{c,i,t-1}\times$ TSc,t $> P_{90}$(TS$_{Europe-c,t}$)						-0.042^{***}	-0.021	0.015	0.018	0.037^{**}
						(0.014)	(0.018)	(0.011)	(0.011)	(0.016)
Log[Rank(Complexity)]$_{c,i,t-1}$	0.018^{***}	0.017^{**}	0.011	0.031^{***}	0.030^{***}	0.016^{***}	0.016^{**}	0.031^{***}	0.031^{***}	0.030^{***}
	(0.007)	(0.007)	(0.010)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
MBPc,t $> \mu$MBP$_{Europe-c,t}$	0.009	0.020	0.129	0.122	0.155^{**}					
	(0.189)	(0.118)	(0.083)	(0.106)	(0.061)					
MBPc,t $> P_{90}$(MBP$_{Europe-c,t}$)$_{c,t}$						0.424^{***}	0.446^{***}	0.716^{***}	0.457^{***}	0.321^{***}
						(0.091)	(0.083)	(0.164)	(0.116)	(0.105)
NMBPc,t $> \mu$NMBP$_{Europe-c,t}$	0.482^{***}	0.169	-0.033	0.115	0.138^{*}					
	(0.148)	(0.132)	(0.065)	(0.102)	(0.072)					
NMBPc,t $> P_{90}$(NMBP$_{Europe-c,t}$)						0.138	-0.087	0.128^{***}	0.132^{***}	0.135^{***}
						(0.177)	(0.301)	(0.038)	(0.032)	(0.033)
TSc,t $> \mu$TS$_{Europe-c,t}$	-0.071	0.041	-0.136	-0.007	-0.032					
	(0.173)	(0.112)	(0.089)	(0.082)	(0.067)					
TSc,t $> P_{90}$(TS$_{Europe-c,t}$)						0.309^{***}	0.155	-0.094	-0.096	-0.187^{**}
						(0.083)	(0.107)	(0.060)	(0.062)	(0.081)
Log[GDP per capita]$_{c,t-1}$	-0.010	-0.006	0.010	0.003	0.002	-0.004	-0.005	0.012^{*}	0.010	0.008
	(0.008)	(0.008)	(0.010)	(0.008)	(0.010)	(0.007)	(0.007)	(0.006)	(0.007)	(0.008)
Log[Trade Openness]$_{c,t-1}$	0.023^{*}	0.026^{*}	0.032^{**}	0.026^{**}	0.026^{***}	0.027^{**}	0.029^{**}	0.022^{**}	0.024^{**}	0.024^{**}
	(0.012)	(0.014)	(0.013)	(0.011)	(0.010)	(0.011)	(0.012)	(0.010)	(0.011)	(0.011)
Border$_{c,i}$	-0.013^{**}	-0.015^{**}	-0.012^{**}	-0.015^{**}	-0.014^{**}	-0.014^{**}	-0.015^{**}	-0.012^{*}	-0.015^{**}	-0.014^{**}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Pioneer$_{c,i}$	-0.025^{**}	-0.026^{**}	-0.022^{*}	-0.027^{***}	-0.030^{***}	-0.026^{**}	-0.029^{***}	-0.025^{**}	-0.025^{**}	-0.025^{**}
	(0.011)	(0.011)	(0.011)	(0.010)	(0.011)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)
Firms count$_{c,i,t-1}$	0.001	0.001	-0.001	-0.001	-0.001	0.0001	0.0003	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
Universities count$_{c,i,t-1}$	0.009	0.011	0.008	0.012	0.014	0.013	0.013	0.017	0.018	0.017
	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)
Log[Green diversification +1]$_{c,t-1}$	-0.020^{***}	-0.021^{***}	-0.012^{**}	-0.009	-0.013^{**}	-0.019^{***}	-0.019^{***}	-0.013^{**}	-0.011^{**}	-0.012^{**}
	(0.006)	(0.006)	(0.005)	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	908	908	908	908	908	908	908	908	908	908
Adjusted R^2	0.916	0.913	0.911	0.912	0.910	0.915	0.913	0.912	0.911	0.911

Note: SE are heteroskedasticity-robust and clustered at the country level. *p<0.1; **p<0.05; ***p<0.01

Results - Take-off phase

	Dependent variable: percentage of trajectory maturity estimated until take-off (10%)									
	Above European average stringency					Strong sringency in Europe				
	EPS t-5	**EPS t-4**	**EPS t-3**	**EPS t-2**	**EPS t-1**	**EPS t-5**	**EPS t-4**	**EPS t-3**	**EPS t-2**	**EPS t-1**
Log[Rank(Complexity)]$_{c,i,t-1}$× MBPc,t > μMBPEurope-c,t	1.925**	0.954	−0.065	−0.261	−0.586					
	(0.785)	(0.932)	(0.802)	(0.996)	(1.012)					
Log[Rank(Complexity)]$_{c,i,t-1}$× MBPc,t > P_{90}(MBPEurope-c,t)						11.627***	10.947***	10.614***	9.297***	5.223*
						(2.273)	(1.957)	(3.008)	(3.508)	(3.109)
Log[Rank(Complexity)]$_{c,i,t-1}$× NMBPc,t > μNMBPEurope-c,t	0.074	0.487	1.334	4.717***	4.514**					
	(0.453)	(0.441)	(1.351)	(1.809)	(1.795)					
Log[Rank(Complexity)]$_{c,i,t-1}$× NMBPc,t > P_{90}(NMBPEurope-c,t)						1.459	2.480***	3.681***	3.474***	3.164***
						(0.969)	(0.883)	(0.614)	(0.687)	(0.768)
Log[Rank(Complexity)]$_{c,i,t-1}$× TSc,t > μTSEurope-c,t	−0.016	0.679	0.084	0.040	0.027					
	(0.671)	(0.785)	(0.552)	(0.255)	(0.467)					
Log[Rank(Complexity)]$_{c,i,t-1}$× TSc,t > P_{90}(TSEurope-c,t)						2.897	3.297	3.292**	1.517	1.976
						(2.923)	(2.699)	(1.512)	(1.749)	(1.405)
Log[Rank(Complexity)]$_{c,i,t-1}$	−2.653***	−2.976***	−2.960**	−4.947***	−4.866***	−3.059***	−3.133***	−4.065***	−3.958***	−3.637***
	(0.755)	(0.770)	(1.210)	(1.569)	(1.779)	(0.746)	(0.677)	(0.933)	(1.038)	(1.085)
MBPc,t > μMBPEurope-c,t	−9.359**	−4.654	0.588	1.718	4.505	−61.976***	−58.804***	−58.425***	−53.335***	−32.054*
	(4.370)	(4.850)	(4.240)	(5.373)	(5.391)	(12.503)	(10.866)	(16.954)	(20.700)	(18.956)
MBPc,t > P_{90}(MBPEurope-c,t)						11.627***	10.947***	10.614***	9.297***	5.223*
						(2.273)	(1.957)	(3.008)	(3.508)	(3.109)
NMBPc,t > μNMBPEurope-c,t	0.850	−1.517	−6.734	−28.171***	−26.300***	−5.783	−10.599***	−15.688***	−15.938***	−15.442***
	(2.461)	(2.487)	(7.685)	(10.262)	(9.733)	(4.446)	(4.053)	(3.620)	(3.230)	(3.275)
NMBPc,t > P_{90}(NMBPEurope-c,t)						1.459	2.480***	3.681***	3.474***	3.164***
						(0.969)	(0.883)	(0.614)	(0.687)	(0.768)
TSc,t > μTSEurope-c,t	−0.903	−5.168	−2.217	−1.344	−0.193	−16.056	−19.489	−21.205	−10.120	−11.768
	(3.845)	(3.955)	(2.388)	(1.234)	(2.167)	(15.103)	(14.339)	(7.803)	(9.848)	(7.819)
TSc,t > P_{90}(TSEurope-c,t)						2.897	3.297	3.292**	1.517	1.976
						(2.923)	(2.699)	(1.512)	(1.749)	(1.405)
RTA$_{c,t-1}$	0.686***	0.628**	0.714**	0.719**	0.665**	0.715***	0.669**	0.734***	0.684**	0.722***
	(0.261)	(0.276)	(0.285)	(0.283)	(0.291)	(0.269)	(0.268)	(0.266)	(0.275)	(0.279)
Firms count$_{c,i,t-1}$	0.678***	0.707***	0.630***	0.622***	0.650***	0.691***	0.634***	0.600***	0.576***	0.543***
	(0.113)	(0.102)	(0.125)	(0.124)	(0.135)	(0.131)	(0.116)	(0.125)	(0.116)	(0.110)
Universities count$_{c,i,t-1}$	0.321	0.308	0.348	0.447**	0.435**	0.501**	0.585**	0.246	0.161	0.225
	(0.301)	(0.293)	(0.256)	(0.179)	(0.212)	(0.252)	(0.257)	(0.237)	(0.276)	(0.281)
Trade Openness$_{c,t-1}$	0.101***	0.108***	0.113***	0.094***	0.093***	0.118***	0.124***	0.116***	0.105***	0.094***
	(0.028)	(0.028)	(0.034)	(0.026)	(0.025)	(0.032)	(0.027)	(0.029)	(0.028)	(0.027)
Green diversification$_{c,t-1}$	0.076	0.063	0.101	0.085	0.047	0.075	−0.006	0.008	0.002	0.056
	(0.093)	(0.097)	(0.093)	(0.088)	(0.081)	(0.101)	(0.119)	(0.095)	(0.098)	(0.089)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Technology FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3,349	3,349	3,349	3,349	3,349	3,349	3,349	3,349	3,349	3,349
Adjusted R^2	0.897	0.897	0.897	0.898	0.898	0.898	0.899	0.899	0.898	0.898

Note: SE are Driscoll-Kraay robust. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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