Three Essays in the Economics of Innovation: Geography, Green Technologies and Policy Uncertainty

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Introduction: Common Themes Across Chapters

- Europe is in search of green growth paths, with the Climate Crisis fueling the need for a new, green industrial policy.
- This thesis attempts to provide empirical evidence able to inform (green) industrial policymaking, by investigating the technological and territorial aspects of globalization and green growth.
  - New industrial policy must consider both territorial aspects and connectivity of regions through FDIs in order to understand this transition (CH1, CH2)
  - Path-dependency in steering innovation requires policies to transition away from fossil path, and uncertainty also plays a role in shaping technological direction (CH3)

Introduction: Common Themes Across Chapters

Evolutionary Economic Geography and Economic Complexity theory are the backbone of this thesis.

- Theoretical foundations:
  - All three chapters share a focus on (directed) technical change as the source for (green) growth (Schumpeter, 1934; Romer, 1990; Aghion and Howitt, 1992).
  - Geography of innovation is the common overarching theme, empirically grounded in patent analysis (Griliches, 1990) and economic complexity methods (Hidalgo, 2021).
  - Integrating spatial and environmental perspectives, this thesis contributes to the broader literature on innovation and regional development.
- Both innovation and the ecological transition have deeply geographical aspects, embedded into technological and path-dependent dynamics.

Core Chapters

- **Chapter 2**: *"Recombinant novelty and Foreign Direct Investments: evidence from European Regions"* (with F. Quatraro, A. Scandura)
- **Chapter 3**: *"Green diversification, global knowledge sourcing and local skill composition: evidence from US cities"* (with F. Fusillo, G. Orsatti, F. Quatraro, A. Scandura)
- **Chapter 4**: *"Climate Policy Uncertainty and Directed Technical Change: evidence from European firms"*

Recombinant Novelty and Foreign Direct Investments: evidence from European Regions

with Francesco Quatraro and Alessandra Scandura

Background

Technological novelty has been a long-standing focus of academic research due to its significant impact on the rate and direction of innovation and technological change.

- Knowledge recombinations staple for ideas creations, mixing existing pieces of knowledge (Nelson and Winter, 1982; Ahuja, 2000; Fleming, 2001; Arthur, 2007)
- In perspective of endogenous growth (Lucas, 1988; Romer, 1990): capability of creating new knowledge entails an economic advantage and opportunity (Feldman and Florida, 1994).

Background

- An increasing number of studies has recently focused on the **impact** of technological novelty. This has proved to be associated to a number of relevant dynamics:
  - Firms' ability to generate impactful innovation and sustain persistent, innovative efforts (Carnabuci and Operti, 2013; Arts and Veugelers, 2015)
  - Increased likelihood of generating environmental friendly patents and regional specialization in green domains (Orsatti et al. 2020, 2023)
  - Changes in the local economic structure (Antonelli 2007; Quatraro 2012)
- Given the relevant effects of technological novelty, some researchers have devoted much effort to improve its **measurement** (Verhoeven et al., 2016; Arts et al., 2021)

Geography of Knowledge Recombination

- Recent stream in economic geography studies the **determinants** of recombinant novelty (Castaldi et al., 2015; Mewes, 2019; Berkes and Gaetani, 2021; Boschma et al., 2021; De Noni and Belussi, 2021)
- We build recent debate on the role of **external connectivity** of regions (Yeung, 2021; Boschma, 2022a). We combine recombinant knowledge approach (Weitzman, 1998; Mewes, 2019) with the economic geography literature on MNEs (Iammarino and McCann, 2013; Cantwell and Iammarino, 2005):
- **IFDI, OFDI, proximity** affect the opportunities for local agents to access heterogeneous pools of knowledge, increasing search space, leading to novel recombination.

Hypotheses: Inward FDIs

- IFDIs are positively related with regional productivity and innovation since they generate **technological spillovers** and **pro-competitive effects** in the receiving region.
- **Spillovers**:
  - MNEs are more productive/innovative, and invest more in R&D than domestic enterprises;
  - Domestic firms benefit from FDI through knowledge transmission (Antonietti et al., 2015; Castellani et al., 2016), tacit complementing explicit (Ernst and Kim, 2002).
  - Agglomerations through co-location of foreign agents can also spur knowledge transfers through geographical spillovers, and as catalysts for innovation (Crescenzi et al., 2022).

Hypotheses: Inward FDIs

- **Pro-competitive effects**:
  - FDIs also have a pro-competitive effect on the host economy as the entry of foreign firms boosts competition in the local market. (Antonietti et al., 2015)
  - Incumbent firms are pushed to search for productivity improvements, and promoting the reallocation of resources toward more productive units.
  - More competitive foreign agents might also put pressure to innovate depending on local firm performance, through crowding out and market-stealing mechanisms (Aitken and Harrison, 1999; Ascani and Gagliardi, 2020).
  - The reallocation of resources may yield negative effects if not performed quickly enough to stay competitive.

Greenfield FDI and Mergers & Acquisitions

- Greenfield FDI builds new operations from scratch, taking more time to establish local linkages and networks.
- M&A leverages existing local knowledge and networks, promoting a more immediate integration into innovation ecosystem.
- Arguably greenfield FDIs have a knowledge-seeking nature, rather than the knowledge exploiting one (Le Bas and Sierra, 2002). M&A arguably of less exploitative nature in developed countries, greenfield more driven by home CA (Harms and Méon, 2018; Davies et al., 2018), pushing exploration and novelty.
- Empirical question crucially concerns **timing**? (Antonietti and Franco, 2021)

Hypotheses: Inward FDIs

- FDIs represent knowledge flows, firms are agents of structural change (Neffke et al. 2018a) creating external linkages for regions in globalized pool of knowledge.
- Knowledge flows contribute to the local knowledge base, potentially introduce novel elements, broaden the technological space and hence possibilities for recombination:
- **Hypothesis 1**: Inward greenfield FDIs are positively associated with recombinant novelty in EU regions

Hypotheses: Outward FDIs

- Outward FDIs are often commonly associated with employment destruction in the home economy, with negative public perception resulting in "reverse mercantilist" view (Iammarino 2018; Gagliardi et al. 2021)
- Much less studied, and recent empirical work has been challenging this view (Crescenzi and Iammarino, 2018; Bathelt and Buchholz, 2019; Ascani et al., 2020).
- Recent evidence on US-OFDIs cautions on increasing spatial inequality.

Hypotheses: Outward FDIs

- Domestic firms that pursue outward FDIs tend to become bigger and more productive compared to purely domestic firms, with effects spilling to regions (Helpman et al., 2004; Bannò et al., 2014; Bathelt et al., 2023). Economies of scale and scope that incentivize investment in R&D activities (Petit and Sanna-Randaccio, 2000).
- Firms engaged in outward FDIs have the chance to improve their ability to source and exploit foreign knowledge (Fosfuri and Motta, 1999).

Hypotheses: Outward FDIs

- However, if firm-level gains fail to offset aggregate losses from offshoring, the net effect may be negative (Castellani and Pieri, 2016).
- Adverse impacts include weakened balance of payments, reduced exports, and negative effects on domestic employment and skills (Crinò, 2009; Gagliardi et al., 2021).
- OFDIs might "hollow out" local resources, harming regional innovation systems (D'agostino, 2015): regional evidence is limited (Bathelt and Buchholz, 2019; Ascani et al., 2020).

Hypotheses: Outward FDIs

In terms of regional novelty, there might be two different effects at play: on the one hand reverse knowledge transfers, coupled with "hollowing-out" of regional knowledge elements.

- There seems to be a competing explanation on the potential impact of outward FDIs on the home economy: both positive and negative outcomes are likely expected:
- **Hypothesis 2a**: Outward greenfield FDIs are positively associated with (local) recombinant novelty in EU regions.
- **Hypothesis 2b**: Outward greenfield FDIs are negatively associated with (local) recombinant novelty in EU regions.

Hypotheses: proximity between FDIs and local capabilities

Lower proximity between IFDIs and regional capabilities provides the building blocks for technological breakthroughs resulting from combinations across unrelated knowledge domains.

- **Hypothesis 3**: The proximity between IFDIs and local capabilities is negatively associated with recombinant novelty.

OFDIs: similarity is measured with respect to the home region. Depending on the mechanism dominating (hollow-out vs reverse knowledge-transfer), we expect two competing effects:

- **Hypothesis 4a**: The proximity between OFDIs and local capabilities is positively associated with recombinant novelty.
- **Hypothesis 4b**: The proximity between OFDIs and local capabilities is negatively associated with recombinant novelty.

Data: Recombinant novelty

- We use REGPAT (OECD) to construct a measure of recombinant novelty based on the appearance of previously unseen pairwise combinations of CPC-4digit sub-classes (Verhoeven et al., 2016).
- We compute novelty at the **local level** (Montresor et al., 2023): combinations never appeared before in the region
  Possible extensions and future robustness:
  - Global measures of novelty (Mewes, 2019; Berkes and Gaetani, 2021).
  - Novelty in knowledge and scientific origins. (Arts and Veugelers, 2015)
  - NLP perspectives could be an interesting firm-level extension on diffusion (Arts et al., 2021).

Data: FDIs and controls

- fDiMarkets (Financial Times) allows us to track greenfield FDIs in bilateral flows.
- Projects are geolocated at the city level and mapped to NUTS3 regions for both source (outward FDIs) and destination (inward FDIs) + R&D vs non-R&D.
- FDI data is aggregated using the perpetual inventory method to account for cumulative effects over time, reduce noise (volatility), measurement error (dates announced).
- **Control variables**: knowledge stock, population density, population size, Variety (UV / RV), regional specialization in manufacturing employment.

Figures: novelty IFDI OFDI

Data: Relatedness density around FDIs

- We map FDIs to technologies (Lybbert and Zolas 2014) and compute two measures to look at how (un)related FDIs are to the local knowledge pool.
- We propose a measure following EEG literature on relatedness, looking at the proximity between FDI technologies and local knowledge specializations (Hidalgo et al. 2018; Montresor and Quatraro 2017)
- **Relatedness-density** of patenting around FDIs. Intuition: the measure increases, the higher the average number of technologies related to FDIs' technologies. details

Descriptive Statistics: link
Correlation Table: link

Baseline model

$$y_{i,t} = \alpha + \beta_1 FDI_{i,t-5} + \mathbf{X}_{i,t-5}\boldsymbol{\beta} + \gamma_i + \theta_t + \epsilon_{i,t}$$

where:

- 1096 NUTS3 regions 2003-2017
- $\mathbf{X}$ is a vector of controls.
- Two-way FE
- 4-years moving averages to tackle patents and FDIs volatility; log-transformed.
- We test different lag structures.
- We add a dummy equal to 1 if FDIs are not present (Aghion et al. 2019).
- Spatial Durbin Models details

Results - FDI

	Novelty									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IFDI	0.0512***	0.0506***	0.0487***	0.0473***	0.0472***					
	(0.0163)	(0.0162)	(0.0162)	(0.0159)	(0.0159)					
OFDI						-0.0422***	-0.0415***	-0.0395***	-0.0355**	-0.0356**
						(0.0146)	(0.0145)	(0.0145)	(0.0145)	(0.0145)
PopDensity	0.7052**	0.6794**	0.7075**	2.211***	2.225***	1.080***	1.049***	1.060***	2.506***	2.521***
	(0.2986)	(0.2983)	(0.2981)	(0.6188)	(0.6210)	(0.2997)	(0.2991)	(0.2986)	(0.6199)	(0.6225)
KnowledgeStock		0.0420	0.0466	0.0457	0.0456		0.0401	0.0448	0.0439	0.0439
		(0.0328)	(0.0325)	(0.0323)	(0.0323)		(0.0329)	(0.0326)	(0.0324)	(0.0324)
Variety			0.7116**	0.6836**	0.6843**			0.6782**	0.6524**	0.6532**
			(0.3163)	(0.3162)	(0.3162)			(0.3151)	(0.3148)	(0.3148)
Population				-1.407***	-1.412***				-1.376***	-1.381***
				(0.5106)	(0.5111)				(0.5214)	(0.5222)
RegSpecialization					0.1214***					0.1276***
					(0.0266)					(0.0263)
Observations	7,952	7,952	7,952	7,952	7,952	7,952	7,952	7,952	7,952	7,952
R^2	0.98222	0.98225	0.98231	0.98237	0.98238	0.98219	0.98222	0.98228	0.98234	0.98234
Within R^2	0.01218	0.01403	0.01764	0.02103	0.02111	0.01095	0.01262	0.01588	0.01909	0.01918
region FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Clustered (region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Results - Relatedness

	Novelty									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Reldensin	-0.3899***	-0.3853***	-0.3713***	-0.3503***	-0.3521***					
	(0.1012)	(0.1014)	(0.1004)	(0.1000)	(0.1001)					
Reldensout						-0.4057***	-0.3987***	-0.3846***	-0.3553***	-0.3565***
						(0.1091)	(0.1087)	(0.1077)	(0.1066)	(0.1067)
PopDensity	0.9408***	0.9110***	0.9312***	2.445***	2.462***	0.8506***	0.8238***	0.8466***	2.374***	2.390***
	(0.2861)	(0.2861)	(0.2859)	(0.6181)	(0.6206)	(0.2873)	(0.2874)	(0.2871)	(0.6204)	(0.6228)
KnowledgeStock		0.0433	0.0479	0.0470	0.0469		0.0409	0.0454	0.0444	0.0444
		(0.0330)	(0.0326)	(0.0324)	(0.0324)		(0.0328)	(0.0324)	(0.0322)	(0.0322)
Variety			0.7235**	0.6950**	0.6957**			0.6851**	0.6559**	0.6567**
			(0.3165)	(0.3163)	(0.3163)			(0.3146)	(0.3144)	(0.3144)
Population				-1.424***	-1.430***				-1.436***	-1.442***
				(0.5140)	(0.5148)				(0.5144)	(0.5151)
RegSpecialization					0.1460***					0.1388***
					(0.0272)					(0.0265)
Observations	7,952	7,952	7,952	7,952	7,952	7,952	7,952	7,952	7,952	7,952
R^2	0.98217	0.98221	0.98227	0.98234	0.98234	0.98224	0.98227	0.98233	0.98240	0.98240
Within R^2	0.00978	0.01175	0.01548	0.01895	0.01906	0.01363	0.01538	0.01872	0.02224	0.02235
region FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Clustered (region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Robustness and heterogeneity

Robustness:

- Alternative construction of FDI variables: IFDI OFDI
- Control for NUTS2-level HRST: HRST
- Relatedness-squared: RelSq
- Timing: IFDI OFDI

Heterogeneity:

- Geographical Breakdown
- R&D
- non-R&D

Spatial Durbin Panel Models:

- Geographical Breakdown
- R&D
- non-R&D

Results - Heterogeneity FDI

Heterogeneity Dimension	Results (IFDI)	Results (OFDI)
Geographical	**EU:** Positive on recombinant novelty, driven by within-EU. **EU15:** Positive and significant. **Non-EU15:** Insignificant or weakly negative.	**EU:** Negative, driven by within-EU. **EU15:** Negative, driven by EU15-EU15 flows. **Non-EU15:** Insignificant or weakly negative.
Spatial Spillovers	Positive local effects, but negative effects in neighboring regions. Direct effects positive also for non-EU15, with stronger indirect effects.	Weak negative direct effects, negative indirect effects for EU15. Positive effects with negative spillovers for nonEU15.
Knowledge intensity	**R&D:** Positive association, driven by within EU IFDI. EU15-EU15 flows with positive spatial spillovers. nonEU15 only profit from EU15, with negative spatial spillovers. Generally, only positive direct effects, weaker negative spatial spillovers. **Non-R&D:** Positive association, driven by within EU IFDI. EU15-EU15 flows with positive spatial spillovers; while nonEU15 profits more.	**R&D:** Weak negative correlations, driven by indirect spatial effects. Insignificant in EU15 and nonEU15. **Non-R&D:** Negative for EU, driven by indirect effects. For EU15, negativity driven by spatial spillovers. For nonEU15, strong positive association for from nonEU15, with large negative spatial spillovers.

Conclusions

- **IFDIs** play a significant role in fostering recombinant novelty by introducing diverse knowledge elements to regional systems (0.04% to 1% increase in number of projects). **OFDIs** show weaker negative association, more nuanced geographically and technologically.
- The correlations vary geographically, with strong **spatial spillovers**, especially for OFDIs, potentially increasing concentration. Negative spillovers are mitigated by knowledge-intensity, but absorptive capacity matters.
- **Proximity** to external knowledge sources negatively correlated with the degree to atypicial recombination in patents.

Green diversification, global knowledge sourcing and local skill composition: evidence from US cities

with Fabrizio Fusillo, Gianluca Orsatti, Francesco Quatraro and Alessandra Scandura

Motivation

- The spatial dynamics underlying the generation of green technological knowledge are fundamental for the green transition.
- Regional green-tech diversification is a key factor to increase growth opportunities, escaping lock-in and achieve a sustainable transition (Montresor and Quatraro, 2020).
- There is an uneven distribution of green specializations across regions both in the US and in Europe (Tanner, 2014, 2016; Santoalha et al., 2021).

Literature Background: role of IFDIs

- Recent literature shows that MNEs' global relationships are crucial for the green transition (Amendolagine et al., 2021; Castellani et al., 2022a; Corrocher et al., 2024)
- Most extant research has addressed the impact of FDIs on environmental performance, while less evidence on FDIs' ability to influence regional technological diversification into green domains.
- Through FDIs, host regions access non-local green knowledge beyond their geographical boundaries, new with respect to the existing one and that can be exploited for the sake of their green-tech transition (Neffke et al., 2018b; Boschma, 2022b)

H1: Inward green FDIs are positively associated with regional technological diversification in green domains

Literature Background: role of capabilities

- Recombinant capabilities are crucial to ensure the effective knowledge recombination for the production of green technological knowledge. (Orsatti et al., 2020, 2023)
- Regional recombinant capabilities depend on **human capital endowment**: the local skill composition influences the ability to support the generation of green technologies.
- Abstract skills correlate with cognitive capabilities to integrate concepts and resources from diverse domains into fresh and unexplored avenues (task-based approach, Acemoglu and Autor (2011)).
- Regional technological green diversification can be favored by higher shares of abstract skills.

H2: The local prevalence of abstract skills is positively associated with regional technological diversification in green domains

Literature Background: external knowledge and skills

- Inward green FDIs and the local occupational structure may interact in two directions, depending on the prevailing type of absorptive capacity in the workforce (Zahra and George, 2002; Mason et al., 2020)
- **Abstract skills**. Potential absorptive capacity (tasks related to knowledge sourcing activities): ability to explore, recognize, acquire and assimilate useful external knowledge.
- **Routine skills**. Realized absorptive capacity (tasks related to knowledge exploitation activities): ability to transform and apply acquired knowledge effectively within organizations.

Literature Background: external knowledge and skills

- Abstract-skills intense occupations act as local brokers of global knowledge, screening across geographically dispersed global knowledge sources, hence compensating for weak flows of incoming FDIs
- **H3a**: The local prevalence of abstract skills compensates for the effects of inwards FDIs on regional green diversification
- Routine-skills intense occupations show distinctive capabilities to translating globally sourced knowledge into marketable new technologies, hence complementing incoming FDIs
- **H3b**: The local prevalence of routine skills augments the effects of inwards FDIs on regional green diversification

Dependent variable

Balanced panel of 287 MSAs observed over the period 2004-2018 (Consoli et al., 2021).

- EntryGT: MSA entry in a new green technological specialization (0/1 dummy)
- Probability of observing a new green specialization in a given MSA
- Based on revealed technological advantage (RTA): Balassa indicator of region's RTA in a given technology
- RTA calculated exploiting the count of USPTO patent applications in any of the IPC and CPC according to OECD-ENVTECH classification.

FDIs

From the fDi Markets database (Financial Times):

- MSA-level FDI inflows in green-related investments
- Geo-localised to the destination city
- Green FDIs (Castellani et al., 2022b): FDIs in industries with RTA in GTs (patent based)
- FDI industries are taken from fDi markets; patents are associated to industries (technological classes-industries); industries are then defined green-tech if specialized in GTs

Map

Skills

- ASH and RSH (dummy based on share of abstract /routine skills)
- Occupations as aggregations of tasks matched with skills required to perform them (Autor et al., 2003; Autor and Dorn, 2013)
- ASH features tasks demanding creativity, intuition, problem-solving and persuasion: (managerial, technical, scientific and creative occupations)
- RSH features repetitive manual or cognitive tasks (clerks, blue collars)
- We calculate the share of employment in ASH/RSH intense occupations over total employment, at the MSA-time level

0/1 dummy = 1 if the share of ASH/RSH skills is above the median share of abstract skills across all MSAs, 0 otherwise.

Map

Controls

- **EmpGrowth**: employment growth rate at MSA-time level
- **GDPpc**: MSA-level per capita gross domestic product
- **ShPatents**: share of MSA patents out of the total level of patenting in the country
- **(d) shGreenEst**: dummy variable taking value 1 if the share of green establishments in a given MSA is above the national median, 0 otherwise
- **GreenPrevRTA**: number of specializations in green technologies for MSA at time t - 1
- **BrownCapex**: 5y moving average of the level of non-green FDI capital expenditure
- **TechRel**: average density of relatedness linkages that new technologies of MSA r shows with respect to pre-existing ones at t - 1

Descriptives Correlation Table

Empirical Strategy I

$$EntryGT_{i,r,t} = \beta_1 GreenCapex_{r,t-1} + \beta_2 ASH_{r,t-1} + \beta_3 RSH_{r,t-1}$$
$$\beta_4 TechRel_{i,r,t} + \psi \boldsymbol{X}_{r,t-1} + \delta_{i,t} + \gamma_s + \epsilon_{i,r,t} \quad (1)$$

$$EntryGT_{i,r,t} = \beta_1 GreenCapex_{r,t-1} + \beta_2 ASH_{r,t-1} + \beta_3 RSH_{r,t-1}$$
$$\beta_4 GreenCapex_{r,t-1} \times ASH_{r,t-1} +$$
$$\beta_5 TechRel_{i,r,t} + \psi \boldsymbol{X}_{r,t-1} + \gamma_s + \delta_{i,t} + \epsilon_{i,r,t} \quad (2)$$

$$EntryGT_{i,r,t} = \beta_1 GreenCapex_{r,t-1} + \beta_2 ASH_{r,t-1} + \beta_3 RSH_{r,t-1}$$
$$\beta_4 GreenCapex_{r,t-1} \times RSH_{r,t-1} +$$
$$\beta_5 TechRel_{i,r,t} + \psi \boldsymbol{X}_{r,t-1} + \gamma_s + \delta_{i,t} + \epsilon_{i,r,t} \quad (3)$$

Empirical Strategy II

- Fixed-effects Logit estimation:
- Year*Tech fixed effects; State fixed effects
- Standard errors clustered at MSA level to account for within-region error correlation
- Continuous variables transformation with inverse hyperbolic function
- Heterogeneity of the results along the value chain
- Robustness checks using share of FDIs (capex and projects)

Results I

	entryGT					
	(1)	(2)	(3)	(4)	(5)	(6)
GreenCapex	0.0436***	0.0267***	0.0366***	0.0222***	0.0406***	0.0058
	(0.0090)	(0.0084)	(0.0080)	(0.0080)	(0.0108)	(0.0092)
BrownCapex	0.0340***	0.0133	0.0321***	0.0197**	0.0219***	0.0215**
	(0.0098)	(0.0089)	(0.0087)	(0.0083)	(0.0083)	(0.0083)
(d) ASH	0.2753***	0.2016***	0.1835***	0.1576***	0.2262***	0.1534***
	(0.0471)	(0.0426)	(0.0400)	(0.0361)	(0.0422)	(0.0357)
(d) RSH	0.0298	0.0463	-0.0107	-0.0283	-0.0343	-0.1140**
	(0.0431)	(0.0396)	(0.0356)	(0.0339)	(0.0333)	(0.0444)
TechRel		0.0143***	0.0143***	0.0125***	0.0126***	0.0126***
		(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
GDPpc			0.2879***	0.1621*	0.1715*	0.1748*
			(0.1009)	(0.0984)	(0.0972)	(0.0984)
EmpGrowth			-0.0453	-0.1767	-0.1754	-0.1563
			(0.3985)	(0.3873)	(0.3841)	(0.3870)
ShPatents			-0.1905***	-0.1755***	-0.1644***	-0.1661***
			(0.0296)	(0.0306)	(0.0296)	(0.0307)
(d) shGreenEst				0.2986***	0.2898***	0.2925***
				(0.0866)	(0.0848)	(0.0852)
GreenPrevRTA				0.6514***	0.6822***	0.6503***
				(0.1841)	(0.1817)	(0.1818)
GreenCapex × (d) ASH					-0.0354***	
					(0.0118)	
GreenCapex × (d) RSH						0.0347***
						(0.0117)
Observations	2,102,562	2,102,562	2,102,562	2,102,562	2,102,562	2,102,562
Log-Likelihood	-108,356.0	-108,022.8	-107,854.2	-107,798.5	-107,786.0	-107,785.0
Adjusted Pseudo R^2	0.06667	0.06953	0.07095	0.07142	0.07151	0.07152
Year*Tech fixed effects	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓

Clustered (MSA) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Results II

	entryGT (4)	(5)	(6)
GreenCapexSupply	0.0213***	0.0386***	0.0040
	(0.0082)	(0.0109)	(0.0100)
GreenCapexDemand	-0.0001	0.0079	0.0051
	(0.0120)	(0.0114)	(0.0122)
BrownCapex	0.0204**	0.0216***	0.0214**
	(0.0084)	(0.0084)	(0.0084)
(d) ASH	0.1573***	0.2223***	0.1534***
	(0.0361)	(0.0413)	(0.0358)
(d) RSH	-0.0280	-0.0350	-0.1087**
	(0.0339)	(0.0333)	(0.0434)
GreenCapexSupply × (d) ASH		-0.0358***	
		(0.0118)	
GreenCapexSupply × (d) RSH			0.0343***
			(0.0120)
Observations	2,102,562	2,102,562	2,102,562
Log-Likelihood	-107,799.3	-107,787.0	-107,786.3
Adjusted Pseudo R^2	0.07140	0.07150	0.07150
Year*Tech fixed effects	✓	✓	✓
State fixed effects	✓	✓	✓
Full controls	✓	✓	✓

Clustered (MSA) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Robustness

Alternative constructions:

- Stocks by Population Stocks PIM Stocks PIM 5% Stocks PIM 10%
- Timing
- Continuous Skills

Additional controls: OFDI, Co-Inventorship, Labour Mobility, Employment Size, Share of Trade Baseline Int ASH Int RSH

Marginal Effects:

- Marginal effects stocks ASH
- Marginal effects stocks RSH

Conclusions

- **Green inward FDIs** positively related to the probability for MSAs to develop new green-tech specialization (+4%).
- New entry in green specialization is higher for cities with above-national levels of **abstract-oriented skills** (odds between 17 and 22%).
- The local skill set can **interact** with IFDIs in supporting diversification:
  - Exploration-oriented skills are crucial for regional green diversification, regardless of the relative weight of green FDIs and can compensate for the lack (or scarcity) of global knowledge sourcing.
  - The presence of workers employed in routine-intense occupations favors the translation of external knowledge into actual innovation.

Climate Policy Uncertainty and Directed Technical Change: evidence from European firms

Motivation

- In the past forty years, scientists have known and stressed the urgent need for climate policies.
- Addressing the climate crisis and achieving Paris Agreements' targets of containing emissions below a 2°C increase, will require a radical policy mix for decarbonization of the world economy (Acemoglu et al., 2012; Rodrik, 2014; Lütkenhorst et al., 2014).
- While progress has been made, their implementation has been subject to a **high degree of uncertainty** (IPCC AR6).
- Consensus and clarity in climate policymaking is a critical factor for success of the transition (Pegels, 2014; van den Bergh, 2023).

Policy uncertainty

- Long tradition on uncertainty and the behavior of economic agents. (Bernanke, 1983; McDonald and Siegel, 1986; Dixit and Pindyck, 1994).
- Baker et al. (2016) measured Economic Policy Uncertainty (EPU) empirically by exploiting newspaper data, leading to much empirical work on effects of policy uncertainty (Cascaldi-Garcia et al., 2023).
- Policy uncertainty has been linked to a decrease in investments, following a "wait-and-see" strategy.

Climate Policy Uncertainty

- CPU quantifies how uncertain the climate-policymaking process is, à la (Baker et al., 2016).
- Wait-and-see in green investments or anticipatory behaviors, net effect is not clear (Pindyck, 2021).
- Uncertainty about government support or policy implementation could slow down particularly green tech (Bettarelli et al., 2023).
- Green tech is more sensitive to EPU and CPU, because of higher tech complexity and risk, dependence on government interventions, relative factor costs (Acemoglu et al., 2012).

Background literature

Evidence focused on effects of CPU (and EPU) on:

- Investments (Dorsey, 2019; Basaglia et al., 2021; Noailly et al., 2022; Berestycki et al., 2022; Hoang, 2022; Hu et al., 2023; Khalil and Strobel, 2023)
- Employment and productivity (Basaglia et al., 2021; Ren et al., 2022; Wang, 2022)
- Emissions (Dorsey, 2019; Gavriilidis, 2021; Wang, 2022).

Work is mostly based on US and China, and evidence on green patenting is mixed (Wang, 2022; Khalil and Strobel, 2023). Some recent evidence on environmental policies and DTC (Gugler et al., 2024).

Hypothesis

- DTC might be affected by relative (expected) cost of green vs dirty investments.
- While we expect EPU to have a negative effect, I expect CPU to crucially depends on direction (Basaglia et al., 2021).
- Arguably, CPU enters firms' production function depending on underlying signals in policy uncertainty (signaling the market future subsidies for EVs or for oil extraction?)
- **Contributions**: new measurement, DTC model, European sample of firms.

Hypothesis 1: Climate Policy Uncertainty affects the direction of technological change in firms, depending on the environemntal direction of the signals underlying it.

Climate Policy Uncertainty

I build a set of web-scrapers to collect full-text newspapers archives (roughly 30 million articles):

- **France**: Le Monde, Le Figaro
- **Germany**: Der Spiegel, Die Zeit
- **Italy**: La Stampa, La Repubblica, Sole24Ore, Il Foglio
- **Spain**: El Pais, El Mundo

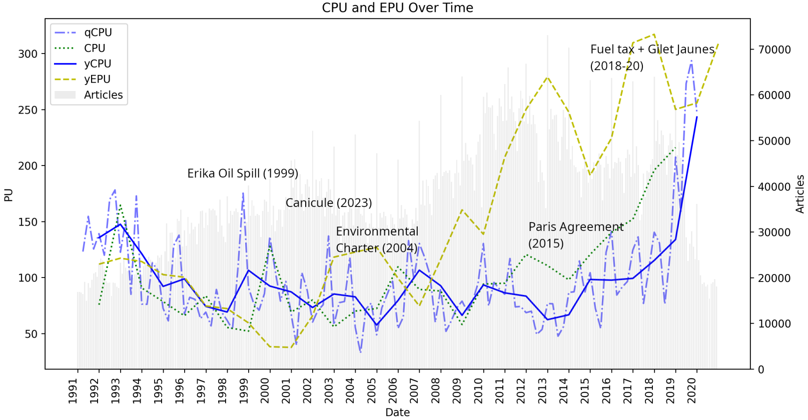
Climate Policy Uncertainty

Match articles based on three sets of keywords:

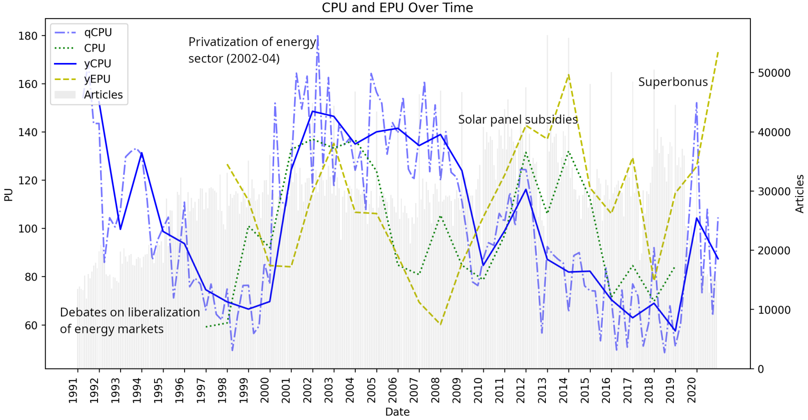
- Climate (e.g. CO2, emissions, global warming).
- Policy (e.g. law, norm, bill).
- Modality set for uncertainty Tobback et al. (2018)

Standard practice: standardize monthly newspaper-level series to unit standard deviation, then average across the papers, then re-scale to 100.

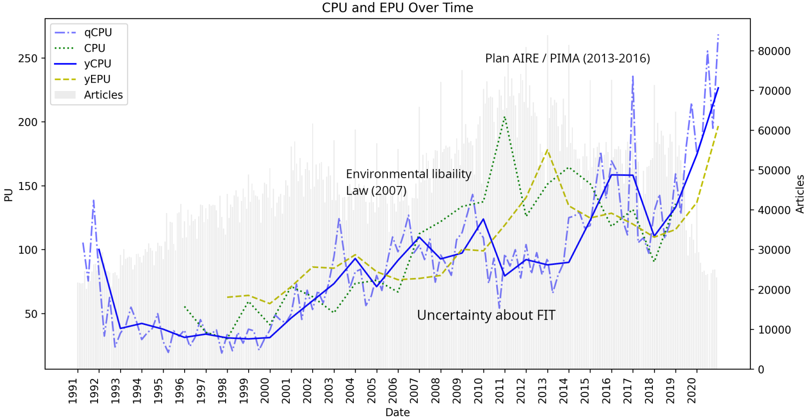
Climate Policy Uncertainty France



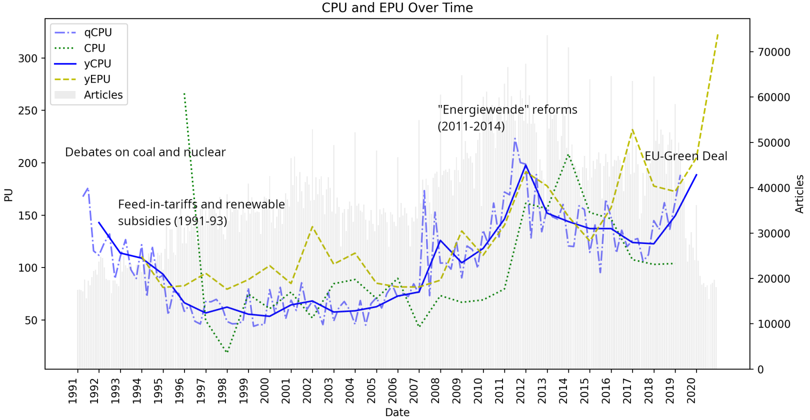
Climate Policy Uncertainty - Italy



Climate Policy Uncertainty - Spain



Climate Policy Uncertainty - Germany



Signals underlying CPU - LLM analysis

- I exploit full-text datasets, annotating text via LLM (OpenAI ChatGPT-4o)
- Promising avenue for labeling (Wang et al., 2024) pros and cons
- Prompts:
  - Q1: *"Is this news article about climate policy issues?"*
  - Q2: *"Does this piece of news imply a strengthening or weakening of climate policy?"*
  - Q3: *"Are the consequences of this news positive or negative for the environment?"*
- *CPUp*: any of Q2 or Q3 imply strengthening.
- *CPUm*: any of Q2 or Q3 imply weakening.
- For conflicting answers I prioritize Q2.
- Alternative indicators of events with peak detection details

Data: Firms and patents

- REGPAT for EPO patents of applicants in the four countries. Triadic Patent Families following Aghion et al. (2016) filed to EPO, USPTO, JPO.
- Matching is performed by searching via Orbis interface applicant names and first match. WIP
- For each firm recognized, I consider firms with at least two patent applications observed in the period 1990-2020. I build an unbalanced panel of firms based available information from Orbis.
- I match **green** patents following the methodology proposed in Favot et al. (2023); **fossil** and **grey** patents extending Dechezleprêtre and Sato (2017) with IEA data.

Data: Controls

- Controls for Economic Policy Uncertainty details
- Share of country-sector patents
- Following Berestycki et al. 2022, I control for sectoral intensity of CO2 emissions (Yamano and Guilhoto, 2020) and OECD's EPS index (Botta and Koźluk, 2014).
- From Orbis I control for firm-size as a categorical variable based on balance-sheet available information. WIP: firms' networks data.
- Dummies for green or dirty stock $= 0$ (Aghion et al., 2016)

Directed Technical Change I

$$PAT_{i,t} = \exp(\alpha + \beta_2 CPU_{i,t-3} + \beta_3 EPS_{c,t-1} * GHG_{c,s,t-1} + \beta_4 K_{i,t-1}) + \eta_i + \tau_{c,t} + \psi_{s,t} + \epsilon_{i,t} \quad (4)$$

- $K_{i,t}$ is the firm's past patent stock;
- $\tau_{c,t}$ are country by year fixed effects;
- $\psi_{s,t}$ are sector by year fixed effects;
- $\eta_{i,t}$ are firm fixed effects;
- $\epsilon_{i,t}$ is the idiosyncratic error term.

$$CPU_{i,t} = \sum_{c \in C} w_{i,c} * CPU_{c,t} \quad (5)$$

$w_{i,c}$ average share of inventors that each firm has in country c. **WIP**: employment and firms as networks.

Directed Technical Change II

- Accounting for path-dependency: stock of total knowledge is sub-divided into green and fossil stocks, and spillovers to the firms (Aghion et al., 2016). details
- The baseline DTC model, with two-way fixed effects would be inconsistent under strict exogeneity, due to serial correlation of patent stocks (Aghion et al., 2016).
- I implement the BGVR (Blundell et al., 1995) estimator relying on the pre-sample mean of the dependent variable in order to proxy-out firm-level fixed effects.

Sample

For the years 1990-2020, the sample totals 4800 firms in 4 countries. Desc Stat. Corr Tab

Table: Sample of Firms by country

Country	Firms	Patents	Green	Dirty	Grey
Germany	2780	163089	13982	12707	3619
Spain	192	4000	327	200	27
France	1112	63740	5142	5285	527
Italy	716	17506	1310	1417	262
Total	4800	248335	20761	19609	4435

Baseline

	Green		Dirty		Grey	
	(1)	(2)	(3)	(4)	(5)	(6)
CPU	0.0658***	0.0660***	0.0908**	0.0870**	0.1180	0.1159
	(0.0138)	(0.0144)	(0.0359)	(0.0348)	(0.0895)	(0.0905)
GreenStock	0.9670***	0.9648***	0.0878***	0.1007***	0.0384	0.0570
	(0.0174)	(0.0174)	(0.0195)	(0.0202)	(0.0529)	(0.0580)
DirtyStock	0.0398***	0.0536***	0.9418***	0.9437***	0.9952***	1.004***
	(0.0121)	(0.0117)	(0.0169)	(0.0166)	(0.0593)	(0.0555)
SPILLgreen	0.4909**	0.5183***	0.1076	0.1245	0.7554	0.8411
	(0.1940)	(0.1958)	(0.3593)	(0.3784)	(0.9403)	(1.004)
SPILLdirty	-0.3984*	-0.4170**	-0.1201	-0.1140	-1.192	-1.243
	(0.2051)	(0.2055)	(0.3660)	(0.3842)	(0.9333)	(1.001)
pre-sample mean	-0.0206***	-0.0066	-0.0468***	-0.0339***	0.0228	0.0351
	(0.0058)	(0.0061)	(0.0089)	(0.0086)	(0.0456)	(0.0494)
Emit	-0.0480	-0.0466	-0.0853	-0.0884	0.4875*	0.5017*
	(0.0639)	(0.0635)	(0.0681)	(0.0660)	(0.2599)	(0.2581)
EPS*Emit	0.0110	-0.0000	0.0449	0.0309	0.2935	0.2620
	(0.0479)	(0.0475)	(0.0484)	(0.0474)	(0.2373)	(0.2236)
ShPatents		-0.0514***		-0.0640***		-0.0926
		(0.0120)		(0.0192)		(0.0742)
Observations	86,562	86,562	82,082	82,082	59,452	59,452
Pseudo R^2	0.65247	0.65321	0.76757	0.76821	0.81496	0.81546
RMSE	0.81964	0.82541	0.86330	0.87008	0.50891	0.51270
Country*Year FE	✓	✓	✓	✓	✓	✓
Industry*Year FE	✓	✓	✓	✓	✓	✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

CPU direction

	Green		Dirty		Grey	
	(1)	(2)	(3)	(4)	(5)	(6)
CPUp	0.6122**	0.6394**	-0.2737	-0.2948	-1.244**	-1.335**
	(0.2510)	(0.2523)	(0.3014)	(0.3120)	(0.6017)	(0.6204)
CPUm	-0.5453**	-0.5718**	0.3654	0.3836	1.354**	1.446**
	(0.2518)	(0.2532)	(0.2959)	(0.3062)	(0.5983)	(0.6123)
GreenStock	0.9671***	0.9649***	0.0877***	0.1007***	0.0378	0.0566
	(0.0174)	(0.0174)	(0.0195)	(0.0202)	(0.0529)	(0.0580)
DirtyStock	0.0397***	0.0536***	0.9418***	0.9438***	0.9957***	1.005***
	(0.0121)	(0.0117)	(0.0168)	(0.0166)	(0.0593)	(0.0555)
SPILLgreen	0.5073***	0.5379***	0.1062	0.1245	0.7106	0.8024
	(0.1944)	(0.1961)	(0.3598)	(0.3797)	(0.9538)	(1.019)
SPILLdirty	-0.4175**	-0.4390**	-0.1173	-0.1117	-1.141	-1.195
	(0.2049)	(0.2052)	(0.3663)	(0.3852)	(0.9472)	(1.019)
pre-sample mean	-0.0207***	-0.0066	-0.0468***	-0.0338***	0.0229	0.0355
	(0.0058)	(0.0061)	(0.0089)	(0.0086)	(0.0456)	(0.0495)
Emit	-0.0477	-0.0464	-0.0838	-0.0868	0.4939*	0.5099**
	(0.0640)	(0.0636)	(0.0680)	(0.0659)	(0.2598)	(0.2579)
EPS*Emit	0.0097	-0.0014	0.0458	0.0319	0.3022	0.2714
	(0.0481)	(0.0477)	(0.0485)	(0.0475)	(0.2387)	(0.2245)
ShPatents		-0.0516***		-0.0643***		-0.0942
		(0.0120)		(0.0192)		(0.0743)
Observations	86,562	86,562	82,082	82,082	59,452	59,452
Pseudo R^2	0.65254	0.65328	0.76759	0.76824	0.81505	0.81557
RMSE	0.81957	0.82535	0.86289	0.86967	0.50835	0.51212
Country*Year FE	✓	✓	✓	✓	✓	✓
Industry*Year FE	✓	✓	✓	✓	✓	✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Alternative measures

	Green		Dirty		Grey	
	(1)	(2)	(3)	(4)	(5)	(6)
RatioP	0.7808**		-0.4563		-1.330*	
	(0.3084)		(0.3831)		(0.7177)	
RatioM	-0.6551**		0.5410		1.424**	
	(0.3076)		(0.3689)		(0.7043)	
PeaksP		0.1190***		-0.0067		-0.0312
		(0.0432)		(0.0512)		(0.0688)
PeaksM		-0.0041		0.1085*		0.2242**
		(0.0460)		(0.0597)		(0.0967)
Observations	72,040	72,040	67,809	67,809	49,725	49,725
Pseudo R^2	0.65688	0.65693	0.76741	0.76745	0.81231	0.81239
RMSE	0.86039	0.86051	0.92261	0.92246	0.52828	0.52888
Country*Year FE	✓	✓	✓	✓	✓	✓
Industry*Year FE	✓	✓	✓	✓	✓	✓
Full Controls	✓	✓	✓	✓	✓	✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Robustness and heterogeneity

- Historical analysis link
- Leave-one-out link
- Weighted regressions link
- Assets assets assets historical
- Timing of effects link
- Magnitude for greentech is around +0.54% for CPU+, -0.51% for CPU-

Research agenda

- Reverse causality and instrumental variable approach.
- Controlling for prices (IEA).
- **Heterogeneity** in technologies green tech (Product Complexity) and sectors (transport vs energy).
- Diversification vs specialization?
- **Heterogeneity** in policy:
  - Content analysis (policies, protests, natural disasters?)
  - Matching of news-based uncertainty to specific sectors?
- **Supply-chain** considerations. Does it affect GT supply-chain techs?
- **Geographical considerations** are largely unexplored from a regional perspective: Policy Uncertainty hits differently regions?

Conclusions

- **CH1:** IFDI and OFDIs as determinants of **recombinant novelty** in European Regions.
- **CH2:** Green IFDIs and skills composition both contribute, and interact, in fostering **green technological diversification** for US Metropolitan State Areas.
- **CH4:** Climate policy uncertainty, according to underlying signals, is a significant factor for **Directed Technical Change**, in European firms.

Conclusions: Policy insights

- **FDI policy**: Tailor regional strategies to attract FDIs that complement local innovation ecosystem, with internationalization not necessarily negative. Crucially consider spatial concentration of innovation as a result of MNE's investments, particularly in the case of OFDIs.
- **Incentivize Green FDIs and skills:** Promote investments enabling diversification into new technological domain; investing in abstract and routine skills understanding local interactions.
- **Reduce uncertainty:** Harmonize climate and industrial policies to reduce uncertainty and foster long-term green innovation, and accelerate the exit from fossil path-dependencies.

Discussion

Thank you!

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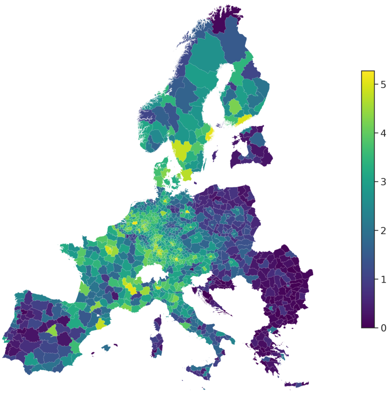
Novelty in NUTS3 regions



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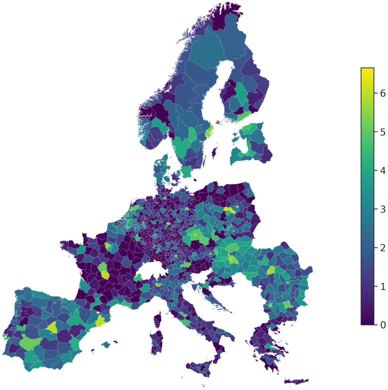
Inward FDIs



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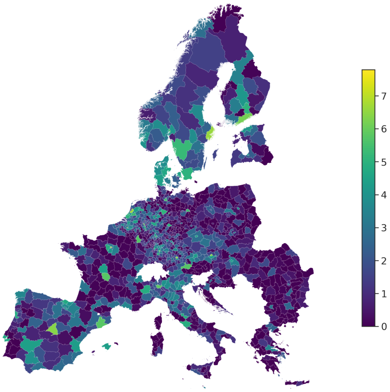
Outward FDIs



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$$\phi_{i,j} = min\{P(RCAx_i|RCAx_j), P(RCAx_j|RCAx_i)\} \tag{6}$$

$\phi_{i,j}$ is the product space (tech-tech proximity from patents).
$\psi_{i,r,t}$, obtaining the relatedness measures for each region-technology pairs:

$$\psi_{i,r,t} = \frac{\sum_{j \in r, j \neq i} \phi_{ij}}{\sum_{j \neq i} \phi_{ij}} \tag{7}$$

$\psi_{i,r,t}$ is relatedness between each technology and the rest of the technologies in the region.
$\omega_{i,r,t}$ as the number of FDIs in technological category i, for that region and year. The count is computed on the stocks of FDIs, and hence compounds in time.

$$reldens\_fdi_{r,t} = \frac{\sum_{j \neq i} \omega_{i,r,t} \psi_{i,r,t}}{\sum_{i \neq j} \omega_{i,r,t}} \tag{8}$$

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Descriptive Statistics

	count	mean	std	min	50%	max
Novelty	17040	20.0	26.7	0.0	11.0	272.0
FDI in	17040	20.6	81.0	0.0	2.0	2,482.0
FDI out	17040	26.4	155.7	0.0	1.0	6,573.0
RelDensityInward	17040	0.1	0.1	0.0	0.0	0.6
RelDensityOutward	17040	0.1	0.1	0.0	0.1	0.8
Population	17040	377,285.6	448,850.9	19,285.0	250,135.5	6,476,838.0
PopDensity	17040	408.2	1,067.1	1.6	127.3	21,490.0
KnowledgeStock	17040	1,177.4	2,451.2	0.0	361.5	35,605.0
Variety	17040	1.0	0.1	0.6	1.0	1.3
RegSpecialization	17040	0.5	0.5	0.0	1.0	1.0
HRST NUTS2	16440	827,738.2	752,094.8	10,124.1	612,339.7	6,846,790.2

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Correlation Table

	Novelty	FDIinward	FDIoutward	RelDensityInward	RelDensityOutward	PopDensity	GDPpercapita	KnowledgeStock	Variety	RegSpecialization
Novelty										
FDIinward	0.34*									
FDIoutward	0.43*	0.76*								
RelDensityInward	0.51*	0.21*	0.24*							
RelDensityOutward	0.58*	0.16*	0.21*	0.58*						
PopDensity	0.35*	0.43*	0.52*	0.19*	0.23*					
GDPpercapita	0.55*	0.17*	0.32*	0.42*	0.48*	0.34*				
KnowledgeStock	0.9*	0.42*	0.54*	0.43*	0.47*	0.41*	0.48*			
Variety	-0.38*	-0.11*	-0.13*	-0.17*	-0.21*	-0.1*	-0.13*	-0.36*		
RegSpecialization	-0.07*	-0.1*	-0.11*	-0.09*	0.01	-0.16*	-0.15*	-0.09*	0.01	

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Spatial econometrics model

$$y_{i,t} = \alpha + \lambda W y_{i,t} + \mathbf{X}_{i,t-5}\beta + W\mathbf{X}_{i,t-5}\beta + \gamma_1 + \gamma_2 + \epsilon_{i,t} \quad (9)$$

where:

- γ_1 are time-fixed
- γ_2 are region-fixed
- ϵ is the idiosyncratic error term
- $\mathbf{X}$ is the vector of control variables
- W is the spatial contiguity matrix

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
netIFDI	0.0323***									
	(0.0088)									
netCapex in		0.0074***								
		(0.0025)								
Capex in			0.0124*							
			(0.0066)							
Capex in PIM5				0.0109*						
				(0.0065)						
Capex in PIM10					0.0092					
					(0.0065)					
Capex per GDP in						0.0187**				
						(0.0088)				
Capex per GDP in PIM5							0.0166*			
							(0.0088)			
Capex per GDP in PIM10								0.0144*		
								(0.0087)		
IFDI noMA									0.0435**	
									(0.0219)	
IFDI										0.0248**
										(0.0118)
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,952	7,952	7,952	7,952	7,952	7,952	7,952	7,952	7,952	7,952
R^2	0.98241	0.98232	0.98233	0.98232	0.98232	0.98234	0.98233	0.98232	0.97359	0.98573
Within R^2	0.02287	0.01821	0.01828	0.01800	0.01775	0.01897	0.01856	0.01819	0.00599	0.02836
region FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Clustered (region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Capex out	-0.0248***							
	(0.0070)							
Capex out PIM5		-0.0240***						
		(0.0069)						
Capex out PIM10			-0.0229***					
			(0.0068)					
Capex per GDP out				-0.0332***				
				(0.0087)				
Capex per GDP out PIM5					-0.0323***			
					(0.0086)			
Capex per GDP out PIM10						-0.0309***		
						(0.0085)		
OFDI noMA							-0.0515***	
							(0.0179)	
OFDI								-0.0131
								(0.0110)
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,952	7,952	7,952	7,952	7,952	7,952	7,952	7,952
R^2	0.98238	0.98237	0.98237	0.98239	0.98239	0.98238	0.97363	0.98567
Within R^2	0.02130	0.02098	0.02062	0.02201	0.02164	0.02121	0.00732	0.02435
region FE	✓	✓	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓	✓	✓

Clustered (region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

back

Control for HRST

	Novelty			
	(1)	(2)	(3)	(4)
IFDI	0.0547***			
	(0.0161)			
OFDI		-0.0317**		
		(0.0148)		
Reldensin			-0.2763***	
			(0.1057)	
Reldensout				-0.3330***
				(0.1071)
Observations	7,672	7,672	7,672	7,672
R^2	0.98209	0.98201	0.98201	0.98202
Within R^2	0.03241	0.02828	0.02851	0.02857
region FE	✓	✓	✓	✓
year FE	✓	✓	✓	✓

Clustered (region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

back

Non-linearity

	Novelty			
	(1)	(2)	(3)	(4)
Reldensin	-0.3131***	-0.4680**		
	(0.0993)	(0.2282)		
Reldensin Sq		0.4462		
		(0.5036)		
Reldensout			-0.3177***	-0.3708
			(0.1064)	(0.2400)
Reldensout Sq				0.1521
				(0.5091)
Observations	7,952	7,952	7,952	7,952
R^2	0.98247	0.98247	0.98253	0.98253
Within R^2	0.02633	0.02646	0.02939	0.02941
Full Controls	✓	✓	✓	✓
region FE	✓	✓	✓	✓
year FE	✓	✓	✓	✓

Clustered (region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

back

Timing IFDI

	Novelty							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IFDI	0.0093	0.0127	0.0167	0.0289*	0.0462***	0.0601***	0.0708***	0.0797***
	(0.0120)	(0.0133)	(0.0145)	(0.0151)	(0.0157)	(0.0164)	(0.0173)	(0.0173)
Observations	12,496	11,360	10,224	9,088	7,952	6,816	5,680	4,544
R^2	0.97918	0.97838	0.97864	0.98026	0.98251	0.98507	0.98763	0.99033
Within R^2	0.19654	0.11028	0.05277	0.02900	0.02865	0.02360	0.01858	0.01756
region FE	✓	✓	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓	✓	✓

Clustered (region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

back

Timing OFDI

	Novelty							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OFDI	0.0175	0.0102	-0.0043	-0.0210	-0.0302**	-0.0291**	-0.0187	0.0053
	(0.0123)	(0.0132)	(0.0138)	(0.0143)	(0.0145)	(0.0148)	(0.0152)	(0.0163)
Observations	12,496	11,360	10,224	9,088	7,952	6,816	5,680	4,544
R^2	0.97924	0.97843	0.97867	0.98031	0.98247	0.98499	0.98752	0.99022
Within R^2	0.19884	0.11221	0.05417	0.03120	0.02636	0.01847	0.01001	0.00597
region FE	✓	✓	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓	✓	✓

Clustered (region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

back

Heterogeneity FDI

	All EU						EU15				nonEU15			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
IFDI	0.0462***													
	(0.0157)													
OFDI		-0.0302**												
		(0.0145)												
EU IFDI			0.0639***											
			(0.0162)											
EU OFDI				-0.0409***										
				(0.0147)										
ROW IFDI					0.0349**									
					(0.0157)									
ROW OFDI						-0.0268								
						(0.0172)								
EU15 IFDI							0.0357**				0.1175**			
							(0.0160)				(0.0561)			
EU15 OFDI								-0.0311**				0.0610		
								(0.0135)				(0.0569)		
nonEU15 IFDI									0.0248				0.0443	
									(0.0170)				(0.0623)	
nonEU15 OFDI										-0.0150				0.0067
										(0.0153)				(0.0634)
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,952	7,952	7,952	7,952	7,952	7,952	6,426	6,426	6,426	6,426	1,526	1,526	1,526	1,526
R^2	0.98251	0.98247	0.98254	0.98247	0.98245	0.98241	0.98404	0.98404	0.98403	0.98400	0.94895	0.94841	0.94860	0.94826
Within R^2	0.02865	0.02636	0.03047	0.02630	0.02548	0.02313	0.01937	0.01893	0.01830	0.01663	0.05068	0.04065	0.04421	0.03778
region FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Clustered (region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Heterogeneity FDI in R&D

	All EU						EU15				nonEU15			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
IFDI	0.0434*													
	(0.0253)													
OFDI		-0.0297*												
		(0.0178)												
EU IFDI			0.1342***											
			(0.0301)											
EU OFDI				-0.0566***										
				(0.0207)										
ROW IFDI					-0.0052									
					(0.0258)									
ROW OFDI						0.0340								
						(0.0401)								
EU15 IFDI							0.1107***				0.0743			
							(0.0329)				(0.0636)			
EU15 OFDI								0.0042				-0.2288		
								(0.0218)				(0.3356)		
nonEU15 IFDI									0.0199				-0.1372	
									(0.0461)				(0.1294)	
nonEU15 OFDI										0.0010				0.2312
										(0.0279)				(0.6974)
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,952	7,952	7,952	7,952	7,952	7,952	6,426	6,426	6,426	6,426	1,526	1,526	1,526	1,526
R^2	0.98244	0.98242	0.98256	0.98243	0.98241	0.98241	0.98409	0.98399	0.98399	0.98399	0.94840	0.94828	0.94833	0.94824
Within R^2	0.02469	0.02341	0.03160	0.02398	0.02303	0.02288	0.02199	0.01623	0.01631	0.01619	0.04044	0.03817	0.03904	0.03748
region FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Clustered (region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Heterogeneity FDI in non-R&D

			All EU					EU15				nonEU15		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
IFDI	0.0508***													
	(0.0157)													
OFDI		-0.0313**												
		(0.0145)												
EU IFDI			0.0674***											
			(0.0161)											
EU OFDI				-0.0392***										
				(0.0147)										
ROW IFDI					0.0453**									
					(0.0182)									
ROW OFDI						-0.0278								
						(0.0172)								
EU15 IFDI							0.0379**				0.1192**			
							(0.0158)				(0.0560)			
EU15 OFDI								-0.0111				0.0798		
								(0.0121)				(0.0673)		
nonEU15 IFDI									0.0280				0.0432	
									(0.0174)				(0.0632)	
nonEU15 OFDI										-0.0142				0.0067
										(0.0154)				(0.0624)
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,952	7,952	7,952	7,952	7,952	7,952	6,426	6,426	6,426	6,426	1,526	1,526	1,526	1,526
R^2	0.98252	0.98247	0.98256	0.98246	0.98247	0.98241	0.98405	0.98401	0.98403	0.98400	0.94893	0.94840	0.94859	0.94826
Within R^2	0.02937	0.02608	0.03136	0.02574	0.02617	0.02314	0.01976	0.01739	0.01834	0.01663	0.05035	0.04035	0.04393	0.03778
region FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Clustered (region) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Spatial Durbin Model - FDI

Pane A:	All EU					
	IFDI	OFDI	EU IFDI	EU OFDI	ROW IFDI	ROW OFDI
Direct Effects						
	0.0409***	0.0001	0.0470***	-0.0104*	0.0322***	0.0025
Indirect Effects						
	-0.0155	-0.0778***	0.0134	-0.0825***	-0.0503**	-0.1465***
Total Effects						
	0.0254	-0.0777***	0.0604**	-0.0930***	-0.0181	-0.1440***
Spatial Coefficient	0.306***	0.297***	0.299***	0.295***	0.3081***	0.2981***
Model	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE
Observations	17040	17040	17040	17040	17040	17040
Adj. R2	0.0948	0.0974	0.0958	0.0981	0.0945	0.0947

Pane B:	EU15				nonEU15			
	EU15 IFDI	EU15 OFDI	nonEU15 IFDI	nonEU15 OFDI	EU15 IFDI	EU15 OFDI	nonEU15 IFDI	nonEU15 OFDI
Direct Effects								
	0.0282***	-0.0142**	0.0201***	-0.0005	0.1708***	0.0880***	0.1206***	0.0626***
Indirect Effects								
	0.0005	-0.0493***	-0.0741***	-0.0531***	-0.0388	-0.1628***	-0.1444***	-0.1395***
Total Effects								
	0.0287***	-0.0635***	-0.0540***	-0.0535***	0.1320**	-0.0748	-0.0238	-0.0769
Spatial Coefficient	0.248***	0.246***	0.249***	0.2521***	0.2817***	0.2837***	0.2727***	0.2707***
Model	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE
Observations	13770	13770	13770	13770	3270	3270	3270	3270
Adj. R2	0.0291	0.0313	0.0296	0.0294	0.1094	0.1028	0.1071	0.0985

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Spatial Durbin Model - FDI in R&D

Pane A:	All EU					
	IFDI	OFDI	EU IFDI	EU OFDI	ROW IFDI	ROW OFDI
Direct Effects						
	0.0267***	0.0086	0.0732***	-0.0076	0.0067	0.0716
Indirect Effects						
	-0.0248	-0.1062***	0.0647	-0.0958***	-0.0891***	0.2092**
Total Effects						
	0.0019	-0.0976***	0.1379***	-0.1034***	-0.0824***	0.2808***
Spatial Coefficient	0.3021***	0.2991***	0.2961***	0.3001***	0.3031***	0.298***
Model	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE
Observations	17040	17040	17040	17040	17040	17040
Adj. R2	0.0934	0.0954	0.0954	0.0942	0.0946	0.0934

Pane B:	EU15				nonEU15			
	EU15 IFDI	EU15 OFDI	nonEU15 IFDI	nonEU15 OFDI	EU15 IFDI	EU15 OFDI	nonEU15 IFDI	nonEU15 OFDI
Direct Effects								
	0.0603***	0.0277**	0.0660***	0.0319**	0.0790***	0.0650	0.0378	0.2854
Indirect Effects								
	0.0992***	-0.0417*	-0.1898***	-0.0230	-0.1299**	-0.9366**	0.2847*	-0.4922
Total Effects								
	0.1595***	-0.0140	-0.1238***	0.0090	-0.0509	-0.8715*	0.3225	-0.2068
Spatial Coefficient	0.2481***	0.2591***	0.2531***	0.2561***	0.2747***	0.2657***	0.2807***	0.2697***
Model	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE
Observations	13770	13770	13770	13770	3270	3270	3270	3270
Adj. R2	0.0312	0.028	0.028	0.028	0.1014	0.0996	0.095	0.0959

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Spatial Durbin Model - FDI in non-R&D

Pane A:	All EU					
	IFDI	OFDI	EU IFDI	EU OFDI	ROW IFDI	ROW OFDI
Direct Effects						
	0.0446***	-0.0016	0.0501***	-0.0109*	0.0474***	0.0023
Indirect Effects						
	-0.0132	-0.0763***	0.0152	-0.0819***	-0.0540*	-0.1492***
Total Effects						
	0.0314	-0.0779***	0.0653**	-0.0928***	-0.0066	-0.1469***
Spatial Coefficient	0.3031***	0.296***	0.304***	0.295***	0.3021***	0.3021***
Model	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE
Observations	17040	17040	17040	17040	17040	17040
Adj. R2	0.0951	0.0973	0.0964	0.098	0.0948	0.0949

Pane B:	EU15				nonEU15			
	EU15 IFDI	EU15 OFDI	nonEU15 IFDI	nonEU15 OFDI	EU15 IFDI	EU15 OFDI	nonEU15 IFDI	nonEU15 OFDI
Direct Effects								
	0.0309***	0.0032	0.0216***	-0.0007	0.1713***	0.0968***	0.1251***	0.0617***
Indirect Effects								
	-0.0034	-0.0246***	-0.0652***	-0.0515***	-0.0272	-0.1256**	-0.1669***	-0.1312***
Total Effects								
	0.0275***	-0.0214**	-0.0435***	-0.0522***	0.1441**	-0.0288	-0.0417	-0.0695
Spatial Coefficient	0.2501***	0.2511***	0.2541***	0.2541***	0.2807***	0.2777***	0.2797***	0.2707***
Model	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE	SDM 2way FE
Observations	13770	13770	13770	13770	3270	3270	3270	3270
Adj. R2	0.0293	0.028	0.0293	0.0294	0.1095	0.0991	0.1091	0.0982

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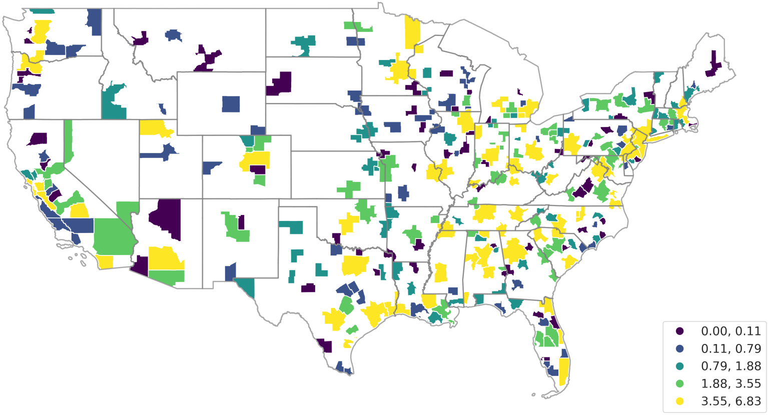

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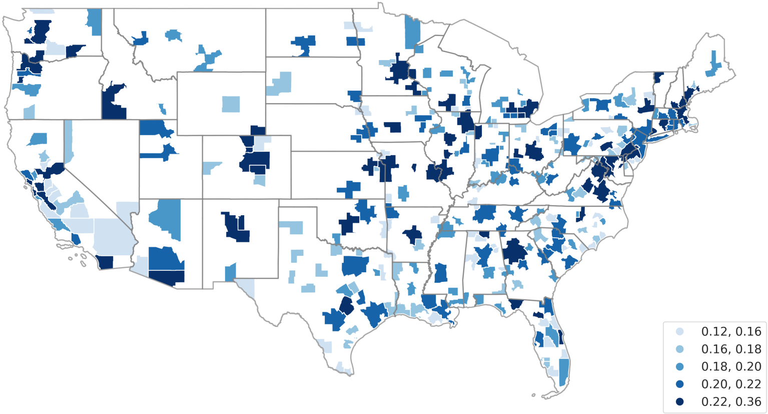

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	N	Mean	St. Dev.	Min	Max
EntryGT	2,472,858	0.010	0.100	0.000	1.000
GreenCapex	2,472,858	55.680	218.190	0.000	3,760.140
BrownCapex	2,472,858	93.190	321.570	0.000	6,107.350
(d) GreenCapex	2,472,858	0.600	0.490	0.000	1.000
(d) BrownCapex	2,472,858	0.760	0.430	0.000	1.000
shGreenCapex	2,472,858	0.170	0.190	0.000	1.000
GreenFDI	2,472,858	0.900	2.380	0.000	27.200
BrownFDI	2,472,858	3.020	12.420	0.000	192.800
ASH	2,472,858	0.200	0.040	0.100	0.400
RSH	2,472,858	0.420	0.050	0.280	0.680
TechRel	2,472,858	10.940	12.800	0.000	100.000
GDPpc	2,472,858	47,174.430	12,821.290	20,320.000	171,389.060
EmpGrowth	2,472,858	0.007	0.032	−0.270	0.206
ShPatents	2,472,858	0.000	0.010	0.000	0.120
shGreenEst	2,472,858	0.010	0.000	0.000	0.020
GTprevRTA	2,472,858	12.790	8.750	0.000	43.000

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	EntryGT	GreenCapex	BrownCapex	(d) GreenCapex	(d) BrownCapex	shGreenCapex	GreenFDI	BrownFDI	ASH	RSH	GDPpc	TechRel	ShPatents	shGreenEst	GTprevRTA
EntryGT															
GreenCapex	0.0*														
BrownCapex	0.01*	0.45*													
(d) GreenCapex	0.02*	0.21*	0.21*												
(d) BrownCapex	0.02*	0.12*	0.16*	0.35*											
shGreenCapex	0.01*	0.31*	0.07*	0.72*	0.26*										
GreenFDI	0.01*	0.5*	0.83*	0.3*	0.19*	0.26*									
BrownFDI	0.01*	0.46*	0.94*	0.18*	0.14*	0.07*	0.89*								
ASH	0.02*	0.06*	0.2*	0.23*	0.21*	0.18*	0.27*	0.22*							
RSH	-0.01*	0.02*	-0.1*	0.01*	-0.05*	0.04*	-0.11*	-0.12*	-0.66*						
GDPpc	0.01*	0.21*	0.3*	0.24*	0.16*	0.13*	0.37*	0.34*	0.51*	-0.14*					
TechRel	0.04*	0.13*	0.23*	0.28*	0.25*	0.21*	0.32*	0.23*	0.33*	-0.17*	0.26*				
ShPatents	0.0*	0.18*	0.46*	0.22*	0.17*	0.08*	0.55*	0.53*	0.46*	-0.25*	0.52*	0.27*			
shGreenEst	-0.0*	-0.1*	-0.09*	-0.25*	-0.22*	-0.25*	-0.15*	-0.08*	-0.08*	-0.12*	-0.16*	-0.11*	-0.13*		
GTprevRTA	0.05*	0.17*	0.23*	0.38*	0.34*	0.35*	0.37*	0.23*	0.39*	-0.18*	0.31*	0.56*	0.21*	-0.14*	

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	entryGT					
	(1)	(2)	(3)	(4)	(5)	(6)
stock GreenCapex (per capita)	0.0326***	0.0201***	0.0239***	0.0130**	0.0230***	0.0028
	(0.0067)	(0.0061)	(0.0061)	(0.0059)	(0.0079)	(0.0068)
stock BrownCapex (per capita)	0.0293***	0.0183***	0.0250***	0.0182***	0.0178***	0.0176***
	(0.0079)	(0.0070)	(0.0069)	(0.0064)	(0.0063)	(0.0064)
(d) ASH	0.3434***	0.2211***	0.2162***	0.1682***	0.2429***	0.1680***
	(0.0430)	(0.0375)	(0.0376)	(0.0322)	(0.0398)	(0.0320)
(d) RSH	0.0366	0.0401	-0.0090	-0.0343	-0.0412	-0.1166***
	(0.0408)	(0.0363)	(0.0331)	(0.0311)	(0.0308)	(0.0403)
TechRel		0.0153***	0.0155***	0.0128***	0.0129***	0.0129***
		(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)
GDPpc			0.3600***	0.1968**	0.2130**	0.2048**
			(0.1009)	(0.0959)	(0.0961)	(0.0969)
EmpGrowth			0.2302	-0.0035	0.0102	0.0288
			(0.3437)	(0.3318)	(0.3301)	(0.3306)
ShPatents			-0.1644***	-0.1622***	-0.1579***	-0.1586***
			(0.0269)	(0.0272)	(0.0268)	(0.0272)
(d) shGreenEst				0.3173***	0.3204***	0.3176***
				(0.0819)	(0.0808)	(0.0807)
GreenPrevRTA				0.8126***	0.8377***	0.8197***
				(0.1808)	(0.1792)	(0.1800)
stock GreenCapex (per capita) × (d) ASH					-0.0216***	
					(0.0079)	
stock GreenCapex (per capita) × (d) RSH						0.0205***
						(0.0075)
Observations	2,867,130	2,867,130	2,675,988	2,675,988	2,675,988	2,675,988
Log-Likelihood	-144,491.0	-143,952.0	-134,711.3	-134,603.9	-134,591.5	-134,592.4
Adjusted Pseudo R^2	0.06682	0.07029	0.07164	0.07236	0.07244	0.07243
Year*Tech fixed effects	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓

Clustered (MSA) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

back

	entryGT					
	(1)	(2)	(3)	(4)	(5)	(6)
stock GreenCapex (PIM)	0.0324***	0.0184***	0.0257***	0.0144**	0.0324***	0.0015
	(0.0073)	(0.0068)	(0.0068)	(0.0066)	(0.0091)	(0.0072)
stock BrownCapex (PIM)	0.0362***	0.0193**	0.0344***	0.0243***	0.0248***	0.0245***
	(0.0089)	(0.0080)	(0.0079)	(0.0075)	(0.0073)	(0.0074)
(d) ASH	0.2818***	0.2000***	0.1865***	0.1580***	0.2584***	0.1564***
	(0.0433)	(0.0384)	(0.0371)	(0.0328)	(0.0397)	(0.0324)
(d) RSH	0.0341	0.0411	-0.0166	-0.0364	-0.0479	-0.1372***
	(0.0399)	(0.0363)	(0.0324)	(0.0311)	(0.0307)	(0.0401)
TechRel		0.0146***	0.0144***	0.0125***	0.0127***	0.0126***
		(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)
GDPpc			0.3303***	0.2004**	0.2246**	0.2142**
			(0.0997)	(0.0966)	(0.0958)	(0.0973)
EmpGrowth			0.1334	-0.0386	-0.0169	0.0090
			(0.3400)	(0.3313)	(0.3288)	(0.3296)
ShPatents			-0.1941***	-0.1817***	-0.1701***	-0.1739***
			(0.0283)	(0.0293)	(0.0281)	(0.0295)
(d) shGreenEst				0.2905***	0.2854***	0.2893***
				(0.0843)	(0.0818)	(0.0824)
GreenPrevRTA				0.6756***	0.7075***	0.6692***
				(0.1838)	(0.1810)	(0.1815)
stock GreenCapex (PIM) × (d) ASH					-0.0333***	
					(0.0086)	
stock GreenCapex (PIM) × (d) RSH						0.0269***
						(0.0075)
Observations	2,867,130	2,867,130	2,675,988	2,675,988	2,675,988	2,675,988
Log-Likelihood	-144,410.2	-143,948.8	-134,662.9	-134,591.1	-134,565.1	-134,572.0
Adjusted Pseudo R^2	0.06734	0.07031	0.07197	0.07245	0.07262	0.07258
Year*Tech fixed effects	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓

Clustered (MSA) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

back

	entryGT					
	(1)	(2)	(3)	(4)	(5)	(6)
stock GreenCapex (PIM 5% discount)	0.0330***	0.0188***	0.0263***	0.0146**	0.0330***	0.0015
	(0.0074)	(0.0068)	(0.0068)	(0.0066)	(0.0092)	(0.0073)
stock BrownCapex (PIM 5% discount)	0.0364***	0.0192**	0.0347***	0.0243***	0.0249***	0.0245***
	(0.0089)	(0.0080)	(0.0079)	(0.0075)	(0.0073)	(0.0074)
(d) ASH	0.2817***	0.2003***	0.1864***	0.1580***	0.2564***	0.1563***
	(0.0433)	(0.0384)	(0.0371)	(0.0328)	(0.0395)	(0.0324)
(d) RSH	0.0339	0.0411	-0.0169	-0.0367	-0.0478	-0.1355***
	(0.0399)	(0.0363)	(0.0323)	(0.0311)	(0.0306)	(0.0399)
TechRel		0.0146***	0.0144***	0.0126***	0.0127***	0.0126***
		(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)
GDPpc			0.3300***	0.2000**	0.2230**	0.2133**
			(0.0995)	(0.0964)	(0.0956)	(0.0971)
EmpGrowth			0.1337	-0.0386	-0.0175	0.0084
			(0.3401)	(0.3313)	(0.3290)	(0.3296)
ShPatents			-0.1942***	-0.1816***	-0.1699***	-0.1737***
			(0.0283)	(0.0293)	(0.0281)	(0.0295)
(d) shGreenEst				0.2915***	0.2857***	0.2902***
				(0.0843)	(0.0818)	(0.0824)
GreenPrevRTA				0.6778***	0.7104***	0.6718***
				(0.1834)	(0.1805)	(0.1811)
stock GreenCapex (PIM 5% discount) × (d) ASH					-0.0338***	
					(0.0088)	
stock GreenCapex (PIM 5% discount) × (d) RSH						0.0273***
						(0.0077)
Observations	2,867,130	2,867,130	2,675,988	2,675,988	2,675,988	2,675,988
Log-Likelihood	-144,412.7	-143,950.4	-134,664.4	-134,592.2	-134,566.9	-134,573.5
Adjusted Pseudo R^2	0.06732	0.07030	0.07196	0.07244	0.07261	0.07257
Year*Tech fixed effects	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓

Clustered (MSA) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

back

	entryGT					
	(1)	(2)	(3)	(4)	(5)	(6)
stock GreenCapex (PIM 10% discount)	0.0335***	0.0191***	0.0267***	0.0148**	0.0334***	0.0014
	(0.0074)	(0.0068)	(0.0069)	(0.0066)	(0.0092)	(0.0074)
stock BrownCapex (PIM 10% discount)	0.0365***	0.0190**	0.0348***	0.0242***	0.0249***	0.0245***
	(0.0088)	(0.0080)	(0.0079)	(0.0075)	(0.0073)	(0.0075)
(d) ASH	0.2817***	0.2007***	0.1863***	0.1580***	0.2539***	0.1563***
	(0.0434)	(0.0384)	(0.0370)	(0.0328)	(0.0393)	(0.0324)
(d) RSH	0.0338	0.0411	-0.0172	-0.0369	-0.0476	-0.1336***
	(0.0399)	(0.0362)	(0.0323)	(0.0310)	(0.0306)	(0.0396)
TechRel		0.0146***	0.0144***	0.0126***	0.0127***	0.0126***
		(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)
GDPpc			0.3299***	0.1996**	0.2213**	0.2123**
			(0.0994)	(0.0963)	(0.0954)	(0.0969)
EmpGrowth			0.1329	-0.0396	-0.0191	0.0069
			(0.3403)	(0.3313)	(0.3292)	(0.3296)
ShPatents			-0.1943***	-0.1814***	-0.1697***	-0.1734***
			(0.0283)	(0.0293)	(0.0282)	(0.0295)
(d) shGreenEst				0.2928***	0.2865***	0.2915***
				(0.0842)	(0.0818)	(0.0824)
GreenPrevRTA				0.6807***	0.7138***	0.6750***
				(0.1830)	(0.1801)	(0.1806)
stock GreenCapex (PIM 10% discount) × (d) ASH					-0.0341***	
					(0.0090)	
stock GreenCapex (PIM 10% discount) × (d) RSH						0.0276***
						(0.0078)
Observations	2,867,130	2,867,130	2,675,988	2,675,988	2,675,988	2,675,988
Log-Likelihood	-144,415.7	-143,952.2	-134,666.4	-134,593.5	-134,569.1	-134,575.3
Adjusted Pseudo R^2	0.06731	0.07029	0.07195	0.07243	0.07260	0.07255
Year*Tech fixed effects	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓

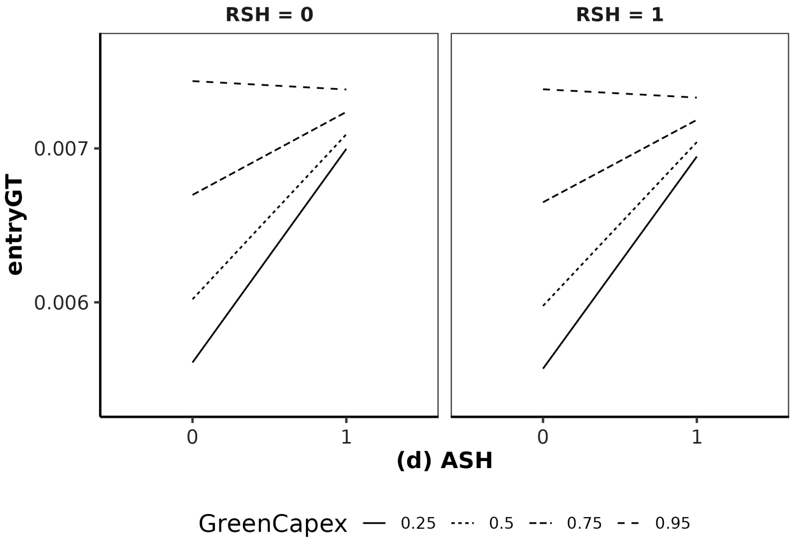
Clustered (MSA) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

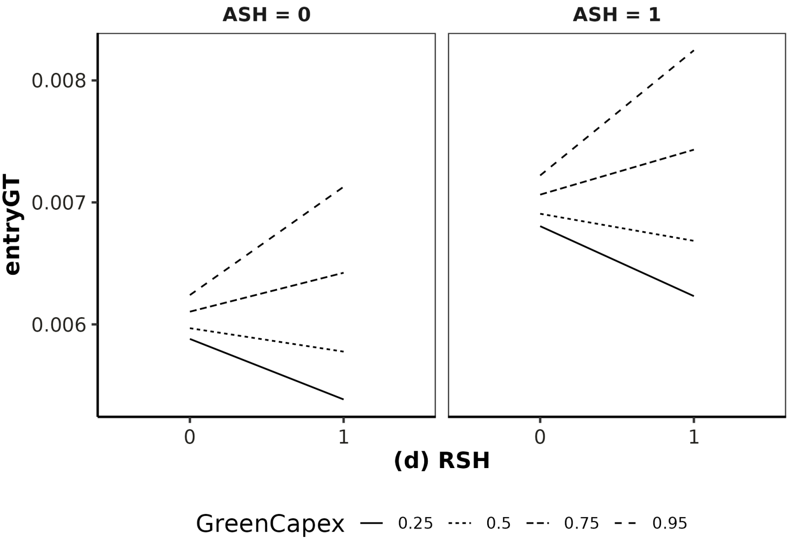
back

	entryGT				
	(t-1)	(t-2)	(t-3)	(t-4)	(t-5)
GreenCapex	0.0222***	0.0225***	0.0190**	0.0230***	0.0204**
	(0.0080)	(0.0083)	(0.0084)	(0.0084)	(0.0088)
BrownCapex	0.0197**	0.0184**	0.0284***	0.0252***	0.0277***
	(0.0083)	(0.0085)	(0.0086)	(0.0084)	(0.0084)
(d) ASH	0.1576***	0.1576***	0.1404***	0.1254***	0.1279***
	(0.0361)	(0.0358)	(0.0367)	(0.0380)	(0.0393)
(d) RSH	-0.0283	-0.0352	-0.0470	-0.0610	-0.0625
	(0.0339)	(0.0355)	(0.0371)	(0.0386)	(0.0410)
Observations	2,102,562	1,911,420	1,720,278	1,529,136	1,337,994
Log-Likelihood	-107,798.5	-98,626.1	-89,406.7	-79,779.6	-69,991.7
Adjusted Pseudo R^2	0.07142	0.06993	0.06937	0.06774	0.06711
Year*Tech fixed effects	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓

Clustered (MSA) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

back


RSH = 0
RSH = 1
entryGT
0.007
0.006
0
1
0
1
(d) ASH
GreenCapex
0.25
0.5
0.75
0.95


ASH = 0
ASH = 1
entryGT
0.008
0.007
0.006
0
1
0
1
(d) RSH
GreenCapex
0.25
0.5
0.75
0.95

back

	entryGT						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GreenCapex	0.0186**	0.0179**	0.0187**	0.0169**	0.0196**	0.0189**	0.0174**
	(0.0084)	(0.0085)	(0.0084)	(0.0083)	(0.0086)	(0.0084)	(0.0086)
BrownCapex	0.0183**	0.0166*	0.0184**	0.0174**	0.0194**	0.0194**	0.0167*
	(0.0088)	(0.0091)	(0.0088)	(0.0088)	(0.0090)	(0.0089)	(0.0091)
(d) ASH	0.1543***	0.1494***	0.1529***	0.1543***	0.1540***	0.1581***	0.1487***
	(0.0364)	(0.0376)	(0.0365)	(0.0365)	(0.0362)	(0.0362)	(0.0381)
(d) RSH	-0.0221	-0.0221	-0.0226	-0.0238	-0.0225	-0.0158	-0.0187
	(0.0363)	(0.0365)	(0.0365)	(0.0361)	(0.0363)	(0.0350)	(0.0349)
OFDI		0.0128					0.0217
		(0.0195)					(0.0242)
Co-inv Patents			-0.0789				-0.0632
			(0.0551)				(0.0545)
LabMobility				0.0330**			0.0312**
				(0.0135)			(0.0137)
Emp					-0.0138		-0.0171
					(0.0223)		(0.0270)
Trade						-0.0314	-0.0271
						(0.0276)	(0.0312)
Observations	2,101,230	2,101,230	2,101,230	2,093,904	2,101,230	2,075,256	2,075,256
Log-Likelihood	-107,466.6	-107,465.7	-107,464.6	-106,959.6	-107,465.8	-106,157.1	-106,146.8
Adjusted Pseudo R^2	0.06997	0.06997	0.06998	0.07009	0.06997	0.06978	0.06983
Year*Tech fixed effects	✓	✓	✓	✓	✓	✓	✓
state_year fixed effects	✓	✓	✓	✓	✓	✓	✓

Clustered (MSA) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

back

	entryGT						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GreenCapex	0.0374***	0.0378***	0.0374***	0.0369***	0.0374***	0.0359***	0.0360***
	(0.0109)	(0.0109)	(0.0110)	(0.0108)	(0.0109)	(0.0111)	(0.0109)
BrownCapex	0.0209**	0.0179**	0.0209**	0.0200**	0.0210**	0.0216**	0.0176*
	(0.0088)	(0.0091)	(0.0088)	(0.0088)	(0.0089)	(0.0089)	(0.0091)
(d) ASH	0.2259***	0.2233***	0.2240***	0.2312***	0.2254***	0.2218***	0.2196***
	(0.0430)	(0.0434)	(0.0432)	(0.0435)	(0.0430)	(0.0431)	(0.0452)
(d) RSH	-0.0284	-0.0291	-0.0289	-0.0310	-0.0284	-0.0224	-0.0260
	(0.0357)	(0.0360)	(0.0358)	(0.0355)	(0.0357)	(0.0345)	(0.0345)
GreenCapex × (d) ASH	-0.0370***	-0.0404***	-0.0367***	-0.0398***	-0.0368***	-0.0336***	-0.0385***
	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0123)	(0.0123)	(0.0125)
OFDI		0.0236					0.0279
		(0.0190)					(0.0231)
Co-inv Patents			-0.0739				-0.0621
			(0.0532)				(0.0538)
LabMobility				0.0366***			0.0339**
				(0.0134)			(0.0138)
Emp					-0.0016		-0.0091
					(0.0228)		(0.0270)
Trade						-0.0247	-0.0226
						(0.0272)	(0.0305)
Observations	2,101,230	2,101,230	2,101,230	2,093,904	2,101,230	2,075,256	2,075,256
Log-Likelihood	-107,453.6	-107,450.9	-107,451.8	-106,944.7	-107,453.6	-106,146.9	-106,134.1
Adjusted Pseudo R^2	0.07007	0.07009	0.07008	0.07021	0.07006	0.06986	0.06993
Year*Tech fixed effects	✓	✓	✓	✓	✓	✓	✓
state_year fixed effects	✓	✓	✓	✓	✓	✓	✓

Clustered (MSA) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

back

	entryGT						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GreenCapex	0.0023	-0.0003	0.0027	-0.0001	0.0028	0.0027	-0.0013
	(0.0097)	(0.0103)	(0.0098)	(0.0096)	(0.0103)	(0.0096)	(0.0101)
BrownCapex	0.0203**	0.0174*	0.0203**	0.0193**	0.0206**	0.0214**	0.0173*
	(0.0088)	(0.0091)	(0.0088)	(0.0088)	(0.0090)	(0.0090)	(0.0092)
(d) ASH	0.1498***	0.1410***	0.1486***	0.1497***	0.1497***	0.1527***	0.1411***
	(0.0360)	(0.0370)	(0.0362)	(0.0362)	(0.0360)	(0.0358)	(0.0376)
(d) RSH	-0.1046**	-0.1110**	-0.1036**	-0.1097**	-0.1036**	-0.0988**	-0.1085**
	(0.0458)	(0.0463)	(0.0459)	(0.0456)	(0.0461)	(0.0451)	(0.0457)
GreenCapex × (d) RSH	0.0338***	0.0365***	0.0333***	0.0352***	0.0334***	0.0340***	0.0372***
	(0.0123)	(0.0127)	(0.0124)	(0.0125)	(0.0127)	(0.0118)	(0.0121)
OFDI		0.0220					0.0282
		(0.0193)					(0.0238)
Co-inv Patents			-0.0698				-0.0523
			(0.0535)				(0.0537)
LabMobility				0.0347**			0.0321**
				(0.0136)			(0.0139)
Emp					-0.0038		-0.0078
					(0.0228)		(0.0271)
Trade						-0.0315	-0.0316
						(0.0287)	(0.0324)
Observations	2,101,230	2,101,230	2,101,230	2,093,904	2,101,230	2,075,256	2,075,256
Log-Likelihood	-107,454.6	-107,452.3	-107,453.1	-106,946.7	-107,454.6	-106,145.3	-106,133.5
Adjusted Pseudo R^2	0.07006	0.07007	0.07007	0.07019	0.07005	0.06987	0.06994
Year*Tech fixed effects	✓	✓	✓	✓	✓	✓	✓
state_year fixed effects	✓	✓	✓	✓	✓	✓	✓

Clustered (MSA) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

back

	entryGT		
	(1)	(2)	(3)
GreenCapex	0.0188**	0.0196**	0.0197**
	(0.0082)	(0.0083)	(0.0083)
BrownCapex	0.0212**	0.0218**	0.0222***
	(0.0084)	(0.0085)	(0.0084)
ASH	0.0779**	0.1151***	0.0838**
	(0.0319)	(0.0357)	(0.0328)
RSH	-0.0100	-0.0095	-0.0348
	(0.0297)	(0.0297)	(0.0301)
GreenCapex × ASH		-0.0181**	
		(0.0083)	
GreenCapex × RSH			0.0156**
			(0.0072)
Observations	2,101,230	2,101,230	2,101,230
Log-Likelihood	-107,474.2	-107,464.1	-107,466.7
Adjusted Pseudo R^2	0.06990	0.06998	0.06996
Year*Tech fixed effects	✓	✓	✓
state_year fixed effects	✓	✓	✓

Clustered (MSA) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

back

LLM limitations and WIP

In comparison with standard keywords and traditional (semi-supervised) machine learning:

- Advantages: multilingual capabilities, time-flexibility of task, syntactic awareness, adapt to longer texts and able to handle common NLP issues (e.g. negation), possibility of teacher-student architecture (Pangakis and Wolken, 2024) (student F1-scores: Q1 at .9, 0.5 to 0.8 Q2/Q3)
- Disadvantages: black box compared to keywords, noise and hallucination remains present, complexity of task decreases precision, non-formal validation of prompts (Berestycki et al., 2022).

WIP: formal validation of prompt-engineering with human labels (Pangakis et al., 2023; Törnberg, 2024), and within ML pipeline. Testing limits to subjectivity and cognitive complexity of task (Juroš et al., 2024) + historical validation. back

Student-Teacher architecture

- LLM annotation as teacher model, fine-tuned smaller machine learning model as student:
  - High reproducibility of GPT-4 labels with a cross-validated accuracy (**F1 at 0.9**).
  - Reduced computational costs while maintaining strong performance.
  - Much lower accuracy with multi-labeling task (train/test setup + cognitive complexity?)
- **Cost-Effective Scalability:** lower costs with high-quality annotation at scale.
- **Cross-Linguistic Applicability:** Multilingual capabilities across language and time.
- **Syntax-Aware Labeling:** mitigate false positives (context and negation, etc.).
- **Dynamic Adaptability:** Enables fine-tuning of models for other datasets and evolving linguistic patterns in journalism.

back

Orbis firm matching

- So far, data collection starts from REGPAT, isolating applicant names.
- Cleaning is performed in terms of near duplicates, and ran through Orbis' propietary name matching engine, first result is extracted.
- Search is restricted only to non-person entities.
- Main limitation regards the lack of network structure in MNE's ownership and locations.
- Currently, working on Orbis Historical and reconstructing network of subsidiaries and GUO.
- Future work exploiting (Arora and Dell, 2023).

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Controlling for EPU

- In the classic idea by (Baker et al., 2016), EPU is proportional to share of Public Procurement in firms/sectors . WIP: ANAC / Open Contracting Partnership / Global Public Procurement Dataset (products-to-NAICS) for cross-country homogeneous controls.
- Alternatively, econometric cleaning of CPU index with autoregressive time-series models (Larsen, 2021; Khalil and Strobel, 2023).

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Path-dependency

$$K_{i,t} = GreenStock_{i,t} + DirtyStock_{i,t} + SPGreen_{i,t} + SPDirty_{i,t} \tag{10}$$

- $GreenStock_{i,t}$ is the firm's own green patent stock;
- $DirtyStock_{i,t}$ is the firm's own dirty patent stock;
- $SPGreen_{i,t}$ are country-level green spillovers to firm i in period t;
- $SPdirty_{i,t}$ are country-level dirty spillovers to firm i in period t;

$$SPGreen_{i,t} = \sum_{c} w_{i,c} * SPGreen_{c,t} \tag{11}$$

$$SPGreen_{c,t} = \sum_{j \neq i} w_{j,c} KGreen_{j,t} \tag{12}$$

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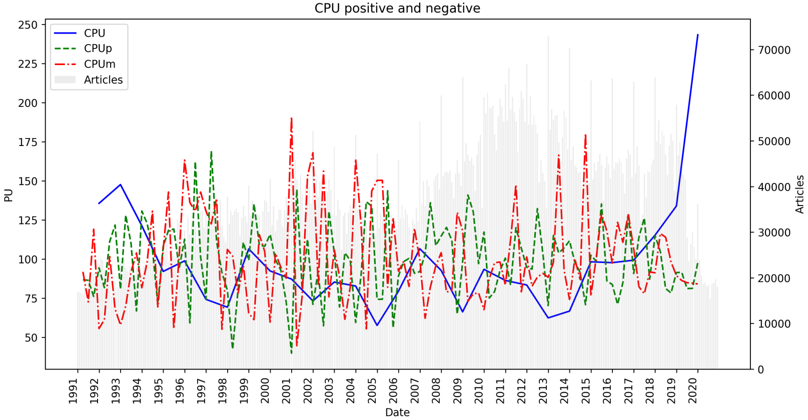
Climate Policy Uncertainty - France



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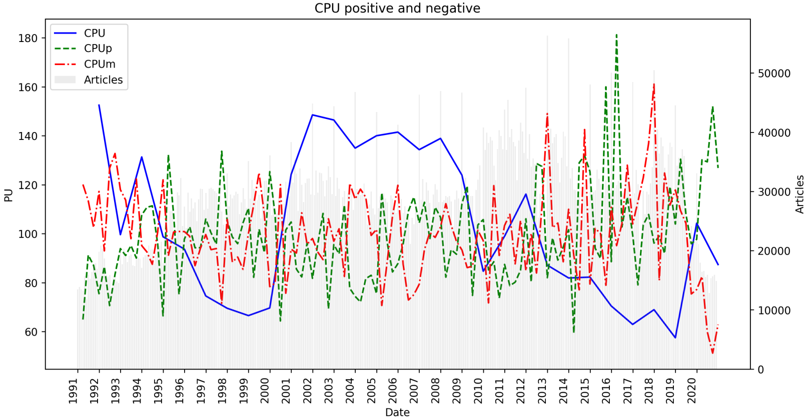
Climate Policy Uncertainty - Italy



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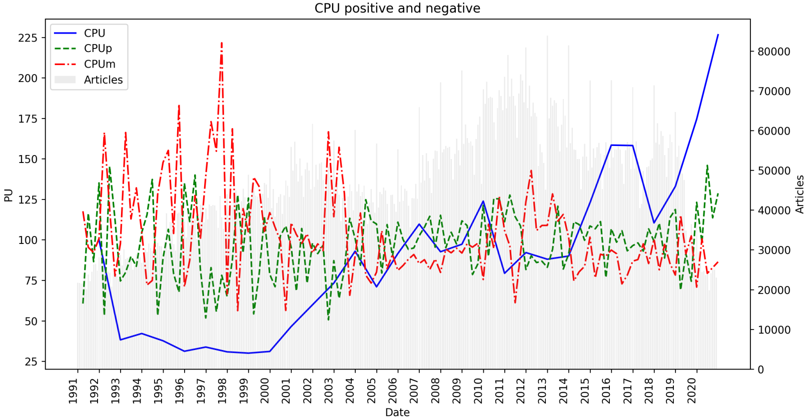
Climate Policy Uncertainty - Spain



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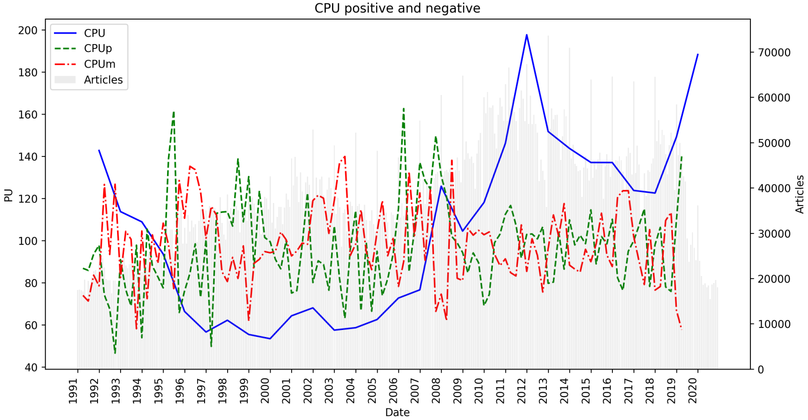
Climate Policy Uncertainty - Germany



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Descriptive Statistics

	Count	Mean	Std	Min	Median	Max
CPU	101919	82.76	45.56	0.00	75.44	243.28
CPUp	101919	81.82	31.45	0.00	88.88	139.97
CPUm	101919	81.31	31.43	0.00	89.42	145.27
Green	101919	0.20	1.71	0.00	0.00	114.00
Dirty	101919	0.17	2.72	0.00	0.00	363.00
Grey	101919	0.04	1.53	0.00	0.00	236.00
Green stock	101919	0.96	7.00	0.00	0.00	356.25
Dirty stock	101919	0.87	11.74	0.00	0.00	1075.12
SPILLGreen	101919	4420.78	3876.12	11.46	3458.82	37151.78
SPILLDirty	101919	3026.18	2312.28	9.43	2620.57	17798.43
EPS	101919	2.45	1.51	0.33	2.46	5.17
Emit	94377	0.02	0.18	0.00	0.00	8.22
ShPatents	94377	0.09	0.24	0.00	0.00	1.00

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Correlation Table

	CPU	CPUp	CPUm	Green	Dirty	Grey	Green stock	Dirty stock	SPILLGreen	SPILLDirty	EPS	Emit	ShPatents
CPU													
CPUp	0.72*												
CPUm	0.62*	0.86*											
Green	0.0*	0.0	0.0										
Dirty	-0.0	0.0	0.0	0.39*									
Grey	-0.0	0.0	0.0	0.22*	0.88*								
Green stock	0.0	-0.01*	-0.01*	0.87*	0.38*	0.2*							
Dirty stock	-0.0	-0.0	-0.0	0.45*	0.88*	0.78*	0.49*						
SPILLGreen	0.04*	-0.15*	-0.19*	0.02*	0.0*	0.0	0.03*	0.01*					
SPILLDirty	0.03*	-0.07*	-0.11*	0.02*	0.01*	0.0*	0.03*	0.01*	0.97*				
EPS	0.14*	-0.08*	-0.2*	-0.0	-0.01*	-0.01*	0.01*	-0.0	0.3*	0.21*			
Emit	0.0	0.0	0.0*	0.01*	0.01*	0.0	0.01*	0.01*	-0.01*	-0.01*	-0.01*		
ShPatents	-0.01*	-0.0	0.0	0.17*	0.1*	0.05*	0.15*	0.1*	-0.03*	-0.03*	-0.04*	0.06*	

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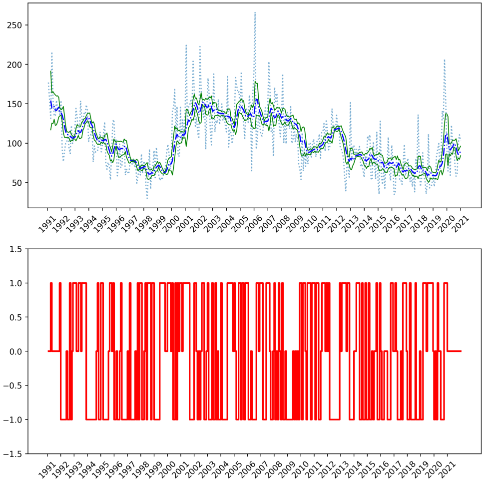
Peak detection - Methodology



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Historical Analysis

	1995-2005			2000-2010			2005-2015			2010-2020		
	Green (1)	Dirty (2)	Grey (3)	Green (4)	Dirty (5)	Grey (6)	Green (7)	Dirty (8)	Grey (9)	Green (10)	Dirty (11)	Grey (12)
CPUp	0.9749**	-0.4172	-0.8527	0.1774	-2.897*	-2.660**	0.2081	0.3255	-2.280**	2.155***	-3.308***	-1.459
	(0.3897)	(0.5638)	(1.130)	(0.6943)	(1.527)	(1.298)	(0.4515)	(0.6777)	(1.048)	(0.8050)	(0.8258)	(1.339)
CPUm	-0.8883**	0.6099	0.9368	-0.1295	3.004*	2.754**	-0.1710	-0.2453	2.339**	-2.121***	3.285***	1.485
	(0.3847)	(0.5533)	(1.112)	(0.6925)	(1.537)	(1.349)	(0.4587)	(0.6781)	(1.087)	(0.8076)	(0.8196)	(1.336)
Num. Firms	3952	3952	3952	4011	4011	4011	3908	3908	3908	3678	3678	3678
Observations	23,107	22,800	18,207	24,069	23,370	18,016	23,594	22,150	16,300	21,560	18,728	11,971
Pseudo R^2	0.60821	0.80119	0.86894	0.67785	0.76176	0.79337	0.68525	0.75026	0.71657	0.64898	0.68547	0.62463
RMSE	0.72646	1.2568	0.67817	1.0306	0.86549	0.39836	1.0658	0.70783	0.37594	0.71811	0.53636	0.28074
Country*Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry*Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Full Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Weighted regressions

	Green		Dirty		Grey	
	(1)	(2)	(3)	(4)	(5)	(6)
CPUp	0.6190*	0.6487*	-0.5998	-0.6014	-1.773**	-1.793**
	(0.3597)	(0.3615)	(0.3840)	(0.4053)	(0.8453)	(0.8381)
CPUm	-0.5311	-0.5518	1.078**	1.074**	2.574***	2.603***
	(0.3538)	(0.3545)	(0.4188)	(0.4322)	(0.8620)	(0.8372)
Observations	86,562	86,562	82,082	82,082	59,452	59,452
RMSE	0.77593	0.77660	0.71955	0.71647	0.37788	0.37771
Country*Year FE	✓	✓	✓	✓	✓	✓
Industry*Year FE	✓	✓	✓	✓	✓	✓
Full Controls	✓	✓	✓	✓	✓	✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Leave-one-out

	Excluding France			Excluding Italy			Excluding Spain			Excluding Germany		
	Green	Dirty	Grey	Green	Dirty	Grey	Green	Dirty	Grey	Green	Dirty	Grey
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CPUp	0.6848**	-0.4028	-1.460	0.4973	-0.8001*	-2.020***	0.7551**	-0.3604	-1.876***	0.5442	-0.3826	-0.3225
	(0.3392)	(0.4092)	(0.9879)	(0.3690)	(0.4502)	(0.7339)	(0.3359)	(0.4096)	(0.6122)	(0.3909)	(0.6181)	(0.7653)
CPUm	-0.6244*	0.4503	1.485	-0.4372	0.8890**	2.140***	-0.6899**	0.4775	1.975***	-0.5086	0.4382	0.3334
	(0.3380)	(0.3960)	(0.9903)	(0.3704)	(0.4458)	(0.7351)	(0.3382)	(0.4119)	(0.6107)	(0.3904)	(0.6020)	(0.7618)
Firms	3229	3229	3229	3572	3572	3572	4007	4007	4007	1705	1705	1705
Observations	55,106	52,403	37,760	61,602	57,937	42,262	69,026	65,217	48,660	26,563	21,544	9,870
Pseudo R^2	0.66901	0.77451	0.83826	0.67090	0.78022	0.82482	0.66006	0.76938	0.81445	0.59669	0.72441	0.62612
RMSE	0.86068	0.84612	0.54918	0.91030	0.95265	0.54967	0.87477	0.93573	0.53189	0.58320	0.80251	0.41412
Country*Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry*Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Full Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Control for EPU

	Green		Dirty		Grey	
	(1)	(2)	(3)	(4)	(5)	(6)
CPUp	0.6803**		-0.4285		-1.645**	
	(0.3099)		(0.3878)		(0.6528)	
CPUm	-0.6011*		0.5408		1.924***	
	(0.3151)		(0.3913)		(0.6860)	
PeaksP		0.1208***		-0.0182		-0.0523
		(0.0452)		(0.0563)		(0.0786)
PeaksM		-0.0144		0.0870		0.2436***
		(0.0493)		(0.0616)		(0.0914)
EPU	-0.0211	0.0073	-0.0374	0.0408	-0.2377***	-0.0474
	(0.0384)	(0.0191)	(0.0569)	(0.0382)	(0.0794)	(0.0585)
Observations	72,040	72,040	67,809	67,809	49,725	49,725
Pseudo R^2	0.65696	0.65713	0.76813	0.76811	0.81637	0.81626
RMSE	0.86229	0.86229	0.92212	0.92288	0.50474	0.50629
Country*Year FE	✓	✓	✓	✓	✓	✓
Industry*Year FE	✓	✓	✓	✓	✓	✓
Full Controls	✓	✓	✓	✓	✓	✓
Firm Size Dummy	✓	✓	✓	✓	✓	✓

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Control for EPS

	Green		Dirty		Grey	
	(1)	(2)	(3)	(4)	(5)	(6)
CPUp	0.6972**		-0.4363		-1.518**	
	(0.3096)		(0.3911)		(0.7262)	
CPUm	-0.6125**		0.5286		1.612**	
	(0.3099)		(0.3848)		(0.7278)	
PeaksP		0.1200***		-0.0091		-0.0483
		(0.0432)		(0.0522)		(0.0766)
PeaksM		-0.0005		0.1113*		0.2342**
		(0.0461)		(0.0593)		(0.1058)
EPS	-0.1253**	-0.0665	-0.0895	-0.0267	-0.2624*	-0.2159*
	(0.0515)	(0.0456)	(0.0668)	(0.0657)	(0.1371)	(0.1145)
Observations	72,058	72,058	67,826	67,826	49,725	49,725
Pseudo R^2	0.65697	0.65704	0.76804	0.76793	0.81585	0.81583
RMSE	0.86151	0.86161	0.91886	0.92111	0.50531	0.50689
Country*Year FE	✓	✓	✓	✓	✓	✓
Industry*Year FE	✓	✓	✓	✓	✓	✓
Full Controls	✓	✓	✓	✓	✓	✓
Firm Size Dummy	✓	✓	✓	✓	✓	✓
Cluster S.E.	Firm	Firm	Firm	Firm	Firm	Firm

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Firm Size controls - continuous variable I

	Green		Dirty		Grey	
	(1)	(2)	(3)	(4)	(5)	(6)
CPUp	0.6705**	0.5162	-0.4072	-0.3593	-1.278*	-1.875**
	(0.3017)	(0.3398)	(0.3780)	(0.3565)	(0.7095)	(0.8080)
CPUm	-0.6132**	-0.4607	0.4919	0.4833	1.345*	1.894**
	(0.3026)	(0.3422)	(0.3713)	(0.3553)	(0.7109)	(0.8109)
FirmSize		0.0276***		0.0266**		-0.0510
		(0.0069)		(0.0108)		(0.0351)
Observations	72,040	54,189	67,809	49,754	49,725	33,203
Pseudo R^2	0.65607	0.67381	0.76690	0.78126	0.81194	0.83452
RMSE	0.85521	0.87632	0.91479	1.0053	0.52534	0.54928
Country*Year FE	✓	✓	✓	✓	✓	✓
Industry*Year FE	✓	✓	✓	✓	✓	✓
Cluster S.E.	Firm	Firm	Firm	Firm	Firm	Firm

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Firm Size controls - continuous variable I

	1995-2005			2000-2010			2005-2015			2010-2020		
	Green	Dirty	Grey	Green	Dirty	Grey	Green	Dirty	Grey	Green	Dirty	Grey
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CPUp	0.9752**	-0.4986	-1.770*	0.4009	-2.895*	-2.461	-0.3040	0.0145	-2.231*	1.609	-2.880***	-3.425**
	(0.4263)	(0.6377)	(0.9877)	(0.7963)	(1.609)	(1.606)	(0.5197)	(0.4939)	(1.204)	(1.089)	(1.048)	(1.597)
CPUm	-0.8955**	0.6755	1.796*	-0.3259	3.001*	2.542	0.3589	0.0945	2.256*	-1.612	3.036***	3.389**
	(0.4208)	(0.6256)	(0.9772)	(0.7960)	(1.621)	(1.668)	(0.5313)	(0.4902)	(1.238)	(1.098)	(1.073)	(1.607)
Firms	3952	3952	3952	4011	4011	4011	3908	3908	3908	3678	3678	3678
Observations	17,550	17,053	11,952	18,151	17,085	12,454	17,785	16,724	11,806	16,059	13,313	7,254
Pseudo R^2	0.62013	0.81964	0.88336	0.69737	0.77435	0.80463	0.70598	0.75700	0.75503	0.66821	0.67966	0.64732
RMSE	0.77335	1.3839	0.72589	1.0113	0.92312	0.41744	1.0401	0.73565	0.35396	0.73663	0.57481	0.29130
Country*Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry*Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Clustered (Firm) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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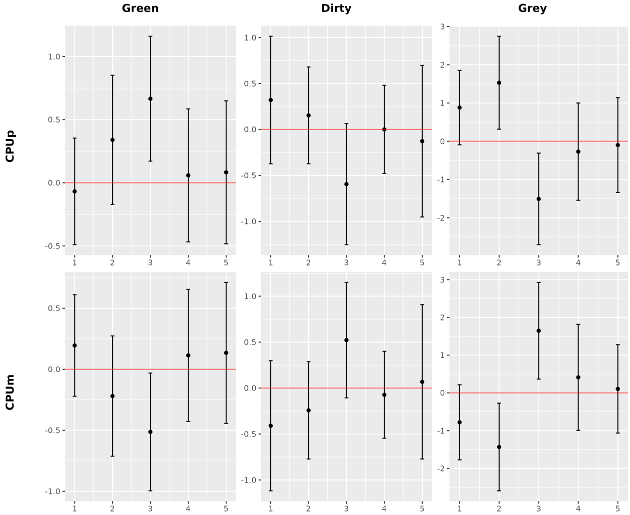
Timing



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