

# Policy choice, timing and stringency and the direction of innovation

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#### FSR CLIMATE ANNUAL CONFERENCE 2022 December 2<sup>nd</sup>, 2022







Disruptive Digitalization For Decarbonization





This work has received funding from European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No 853487).

## <u>Outline</u>

- The paper in a nutshell
- Motivation
- Competing models of the direction of technical change
- Econometric implementation and data
- Empirical results
- Simulation and discussion

## The paper in a nutshell

## In a nutshell

- <u>What</u>: We test whether and how the effectiveness of environmental policy instruments in promoting a radical technology depends on the level of existing "competencies"-i.e. the knowledge stocks
- <u>How</u>: We develop three alternative models and choose the one that best fits the data
- <u>Results</u>: Competencies mediate policy effectiveness in a non-linear way, giving rise to different policy effectiveness regimes.
- <u>Relevance</u>: the effectiveness of a given policy instrument depends on the level of competences, the timing of policy choice and policy stringency

 $\rightarrow$  If you choose the wrong policy instrument, or time it wrongly, innovation benefits related with policies will not accrue

## Motivation

#### Motivation

<u>The idea is not new:</u> appropriate policy choice is contingent on the stage of technological development of a country

- Rodrick (2005) on appropriate growth strategy
- Rich literature explores poverty traps and multiple equilibria as a function of policies affecting accumulation of physical or human capital and technologies)
- In Acemoglu et al. (2006) the choice of the appropriate policy depends on the distance to the technological frontier

<u>But we give it a twist</u>: Policy effectiveness in promoting innovation, and directing it towards a radical innovation rather than an incremental one, is not independent from the relative specialization of a country in these two technological domains. Furthermore, there is not reason to exclude that the mediating role of specialization is non linear.

Why giving it a twist? BECAUSE WE NEED TO PROMOTE RENEWABLE ENERGY INNOVATION

#### Motivation



(based on IPCC-assessed scenarios)



Competing models of the direction of technical change

#### Theoretical framework

1<sup>st</sup> building block: Knowledge production function

$$k = A K^{\beta_K} \mathbf{C}^{\mathbf{B}_{\mathbf{C}}} e^{\mathbf{B}_{\mathbf{P}} \times \mathbf{P} + v}$$

2<sup>nd</sup> building block: Heterogeneity in research domains

$$k_d = A_d K_d^{\beta_K} {}^{_d} K_{-d}^{\beta_{K-d}} \mathbf{C}^{\mathbf{B}_{\mathbf{d},\mathbf{C}}} e^{\mathbf{B}_{\mathbf{d},\mathbf{P}} \times \mathbf{P} + \upsilon_d}$$

In the context of radical and incremental energy technologies:

$$\begin{cases} k_g = A_g K_g^{\beta_{K_g}} K_{-g}^{\beta_{K_{-g}}} \mathbf{C}^{\mathbf{B}_{\mathbf{g},\mathbf{C}}} e^{\mathbf{B}_{\mathbf{g},\mathbf{P}} \times \mathbf{P} + \upsilon_g} \\ k_f = A_f K_f^{\beta_{K_f}} K_{-f}^{\beta_{K_{-f}}} \mathbf{C}^{\mathbf{B}_{\mathbf{f},\mathbf{C}}} e^{\mathbf{B}_{\mathbf{f},\mathbf{P}} \times \mathbf{P} + \upsilon_f} \end{cases}$$

## Three alternative models

Linear  

$$K_{-(g+f)} = K - K_g - K_f$$

$$\ln rk = \ln rA + \beta_{K_g} \ln rK - \beta_{Kf'} \ln K_f + \beta_{K_{-(g+f)}} \ln K_{-(g+f)} + \mathbf{B}_{\mathbf{C}} \ln \mathbf{C} + \mathbf{B}_{\mathbf{P}} \mathbf{P} + \epsilon.$$

$$K_{-(g+f)} = K - K_g - K_f$$

$$\beta_{K_f} = \beta_{K_g} + \beta_{K_{f'}}$$

$$\beta_{K_f} > \beta_{K_g} (\text{resp. } \beta_{K_f} < \beta_{K_g})$$
Interaction  

$$\ln rk = \ln rA + \beta_{K_g} \ln rK + \mathbf{B}_{\mathbf{P}} \mathbf{P} + \mathbf{B}_{\mathbf{K}_g, \mathbf{P}} (\ln rK \times \mathbf{P})$$

$$- \beta_{Kf'} \ln K_f + \beta_{K_{-(g+f)}} \ln K_{-(g+f)} + \mathbf{B}_{\mathbf{C}} \ln \mathbf{C} + \epsilon.$$

$$\partial \ln rk / \partial \ln \mathbf{P} = \mathbf{B}_{\mathbf{P}} + \mathbf{B}_{\mathbf{K}_g, \mathbf{P}} \times \ln rK$$

 $rk = k_g/k_f$  $\mathbf{B}_{\mathbf{P}} = \mathbf{B}_{\mathbf{g},\mathbf{P}} - \mathbf{B}_{\mathbf{f},\mathbf{P}}$ 

 $K_{-q} \simeq K_{-f} \simeq K_{-(q+f)}$ 

Threshold

 $\ln rk = \ln rA + \beta_{K_g} \ln rK + \mathbf{B_{1P}P} \times \mathbf{I_1}(\gamma_1, \gamma_2) + \mathbf{B_{2P}P} \times \mathbf{I_2}(\gamma_1, \gamma_2) + \mathbf{B_{3P}P} \times \mathbf{I_3}(\gamma_1, \gamma_2)$ 

 $-\beta_{Kf'} \ln K_f + \beta_{K_{-(g+f)}} \ln K_{-(g+f)} + \mathbf{B}_{\mathbf{C}} \ln \mathbf{C} + \epsilon,$ 

## Two demand-pull policy instruments

<u>Command-and-control</u>: Impose limits on the level of pollution of requirements

- Limits on emissions
- Green certificates

<u>Market-based</u>: impose an implicit or explicit price on emissions

- Carbon-tax
- Emission trading scheme

Latter preferred by economic theory on efficiency grounds (static vs dynamic) But: no strong empirical evidence, criticism by social scientists

#### $\rightarrow$ WE SPLIT THE POLICY VECTOR IN TWO

# Econometric implementation and data

## Econometric implementation

Challenges, which we address in the analysis:

- 1. (a) Accounting for <u>unobserved heterogeneity</u> in the context of slowly changing policy variables and (b) <u>endogeneity</u> of the policy variables: *control function and IV*
- 2. Implementing an empirical strategy to <u>search for thresholds effects</u>: *Hansen's threshold method*
- 3. Developing a <u>model selection procedure</u> to compare the performance of different models: *R-squared, Vuong's 2LR statistics on overlapping models, Akaike information criterion (AIC) with a correction for small samples (AICC)*

#### Data

- Econometric analysis: balanced panel of 33 countries, 1990-2015
- <u>Innovation</u>: Patent data from PATSTAT, using classification in renewable and efficient fossil as standard in the field
- <u>Threshold variable</u>: ratio of K stocks (perpetual inventory method)
- <u>Policy indexes</u>: EPS index for MB and C&C (instrumented via a shift-share approach) IV approach to account for endogeneity
  - Reverse causality: policy response depends positively on present and future competence of the country ( $\uparrow$ )
  - Measurement error in the policy variables (  $\downarrow$  )
  - Omitted variable bias (fossil subsidies) ( $\downarrow$ )
- <u>Standard controls</u> in the literature (el. consumption p/c, el. imp. & exp. shares, human capital index, GDP, pop)









# **Empirical results**

Results		Linear $1P$ Eq.(4) (1)	$ \begin{array}{c} \text{Linear } 2P \\ \text{Eq.}(4) \\ (2) \end{array} $	Interaction Eq.(5) (3)		Threshold Eq.(7) (4)
Two discontinuities → three regimes (47 <sup>th</sup> ,89 <sup>th</sup> )	$\ln r K_{g/f,t-1}$ $\ln K_{f,t-1}$ $\ln K_{-(f+g),t-1}$	$\begin{array}{c} 0.400^{***} \\ (0.122) \\ 0.003 \\ (0.164) \\ 0.144 \\ (0.111) \end{array}$	$\begin{array}{c} 0.411^{***} \\ (0.116) \\ -0.046 \\ (0.120) \\ 0.139 \\ (0.095) \end{array}$	$\begin{array}{c} 0.225^{**} \\ (0.114) \\ -0.061 \\ (0.118) \\ 0.172^{*} \\ (0.092) \end{array}$	$\ln r K_{g/f,t-1}$ $\ln K_{f,t-1}$ $\ln K_{-(f+g),t-1}$	$\begin{array}{c} 0.258^{**} \\ (0.108) \\ -0.080 \\ (0.125) \\ 0.176^{*} \\ (0.095) \end{array}$
MB instrument effective only in strengthening current specialization, consolidate comparative advantage	ALL policies MB policies $MB \times \ln rK_{g/f,t-1}$ CC policies $CC \times \ln rK_{g/f,t-1}$	0.158 (1.999)	$\begin{array}{c} 0.129 \\ (0.391) \end{array}$ 1.161** $(0.510) \end{array}$	$\begin{array}{c} -1.408^{*}\\ (0.735)\\ 0.837^{*}\\ (0.492)\\ 0.816\\ (0.645)\\ 0.202\\ (0.353)\end{array}$	$\begin{split} MB \times \mathbf{I}(\ln r K_{g/f,t-1} &\leq \hat{\gamma}_1^r) \\ MB \times \mathbf{I}(\hat{\gamma}_1^r < \ln r K_{g/f,t-1} \leq \hat{\gamma}_2) \\ MB \times \mathbf{I}(\ln r K_{g/f,t-1} > \hat{\gamma}_2) \\ CC \times \mathbf{I}(\ln r K_{g/f,t-1} \leq \hat{\gamma}_1^r) \\ CC \times \mathbf{I}(\hat{\gamma}_1^r < \ln r K_{g/f,t-1} \leq \hat{\gamma}_2) \end{split}$	-0.692 (0.576) -0.021 (0.506) 1.680* (0.947) 1.130** (0.499) 1.371** (0.628)
<i>Third regimes</i> : top 11 percent	$\begin{array}{c} F\text{-stat IV } ALL \\ F\text{-stat IV } MB \\ F\text{-stat IV } CC \end{array}$	70.51	45.73 65.94	45.73 65.94	$\begin{array}{c} CC \times \mathbf{I}(\ln r K_{g/f,t-1} > \hat{\gamma}_2) \\ \\ \hline F\text{-stat IV } ALL \\ F\text{-stat IV } MB \\ F\text{-stat IV } CC \end{array}$	$ \begin{array}{r} 0.609 \\ (0.789) \\ 45.73 \\ 65.94 \end{array} $

# Simulation

## Simulation

- BLACK: reproduces observed
- GREY: if policies had been introduced with observed stringency but correct timing
- RED: if policies had been introduced with maximum stringency AND correct timing



## In a nutshell

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## Thank you.

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### Results

	$\hat{\gamma}_1^r$	$\hat{\gamma}_2$	<u> </u>
Threshold percentile Threshold value for $\ln r K_{g/f,t-1}$ 95 % CI for $\ln r K_{g/f,t-1}$ 90 % CI for $\ln r K_{g/f,t-1}$ F-statistics P-value	$\begin{array}{c} 47\\ 1.292\\ [0.929,\ 1.336]\\ [1.219,\ 1.336]\\ 25.260\\ 0.001\end{array}$	89 2.198 [2.161,NA] [2.147,NA] 21.430 0.010	$\begin{array}{c} 32 \\ 1.033 \\ [.457,  1.154] \\ [.491,  1.120] \\ 10.140 \\ 0.126 \end{array}$

Table A1: First Stage Tobit Regressions						
	(1)	(2)	(3)			
	ALL	MB	CC			
Pre-sample mean	0.061*** (0.018)	$0.086^{***}$ (0.025)	$0.057^{**}$ (0.023)			
$\ln r K_{g/f,t-1}$	$0.013 \\ (0.011)$	$\begin{array}{c} 0.147^{***} \\ (0.019) \end{array}$	-0.041*** (0.016)			
$\ln K_{f,t-1}$	$\frac{0.033^{**}}{(0.013)}$	$0.158^{***}$ (0.025)	-0.022 (0.018)			
$\ln K_{-(g+f),t-1}$	-0.023** (0.010)	$-0.129^{***}$ (0.019)	$0.024^{*}$ (0.014)			
IV <sub>ALL</sub>	0.880*** (0.070)					
$IV_{MB}$		$\begin{array}{c} 1.441^{***} \\ (0.175) \end{array}$	$0.063 \\ (0.140)$			
$IV_{CC}$		-0.230** (0.109)	$0.912^{***}$ (0.078)			
Control variables	Yes	Yes	Yes			
Observations	759	759	759			
Observations left censored	85	280	132			
Observations right censored	0	1	8			
F-stat IV	70.51	45.73	65.94			

#### Results