What determines the adoption of renewable energies across countries?

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2018

Structure

- Introduction
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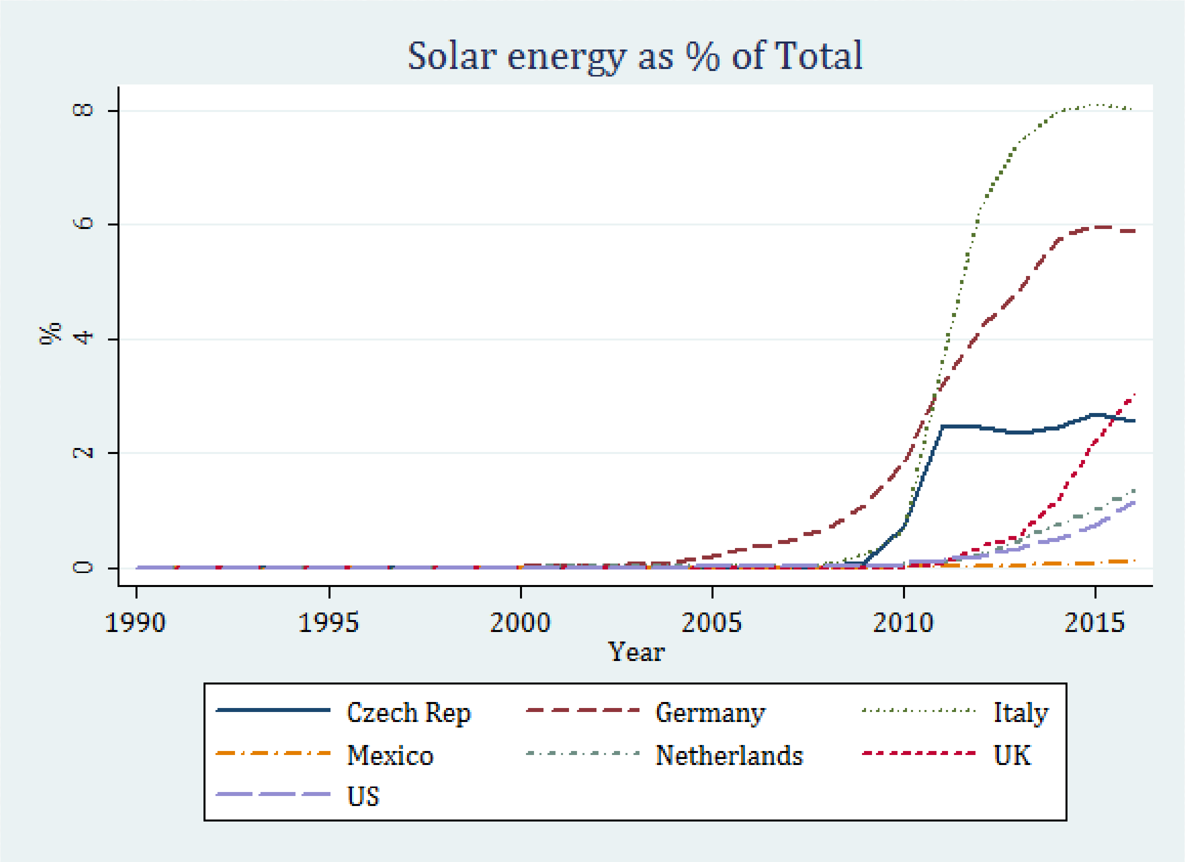
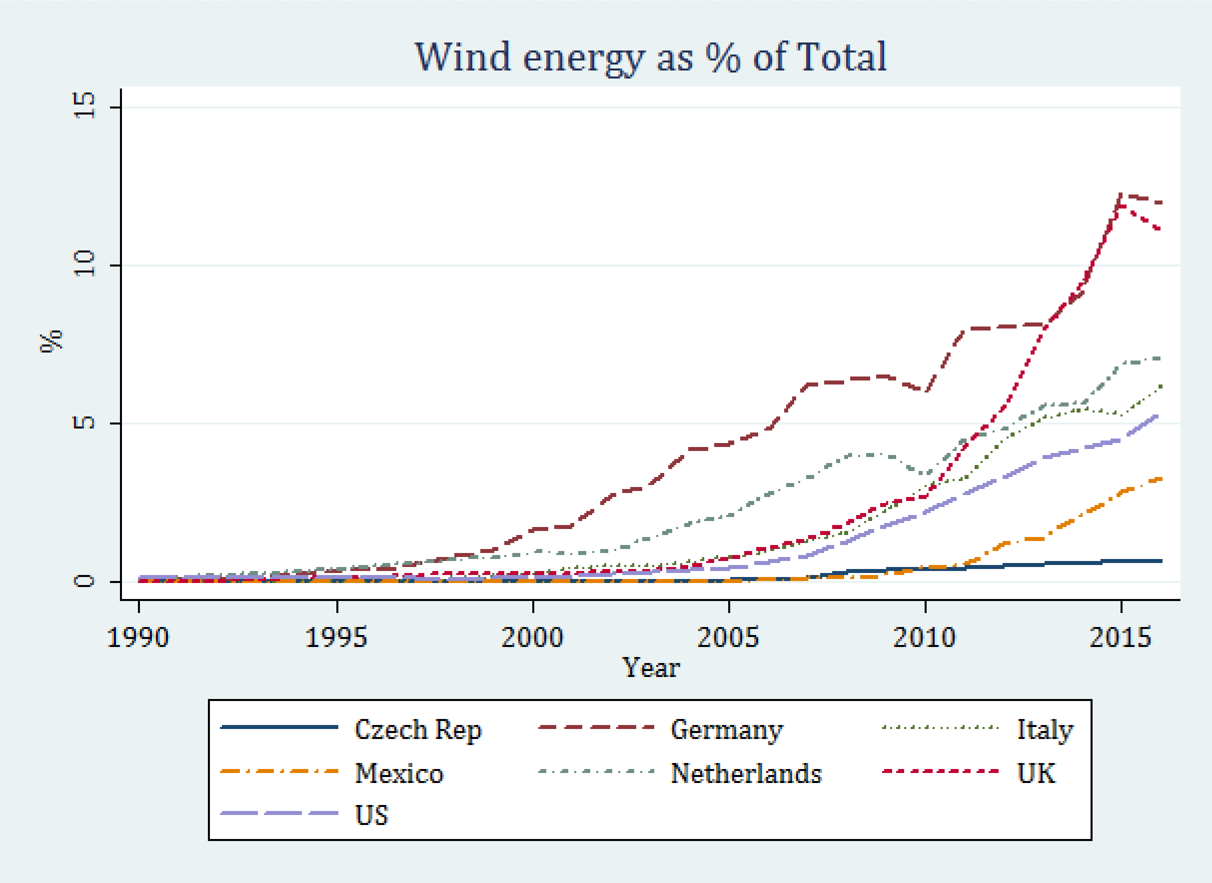
Adoption of solar renewable energy production



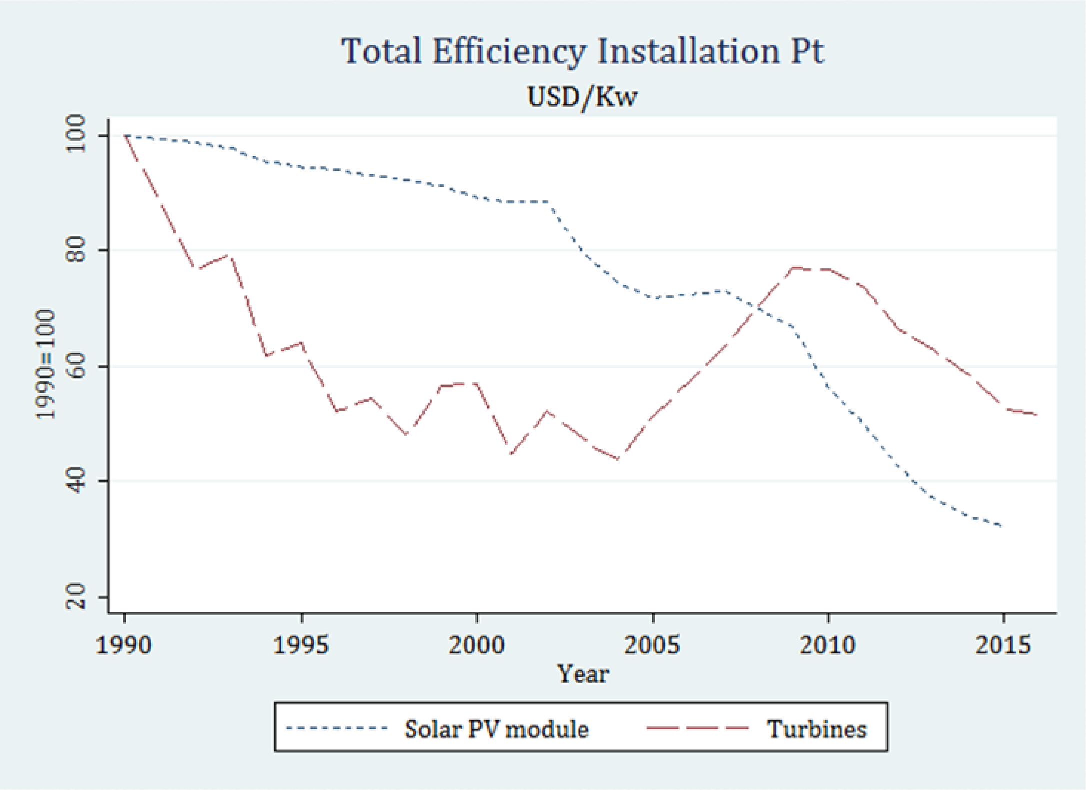
Source IEA (2017)

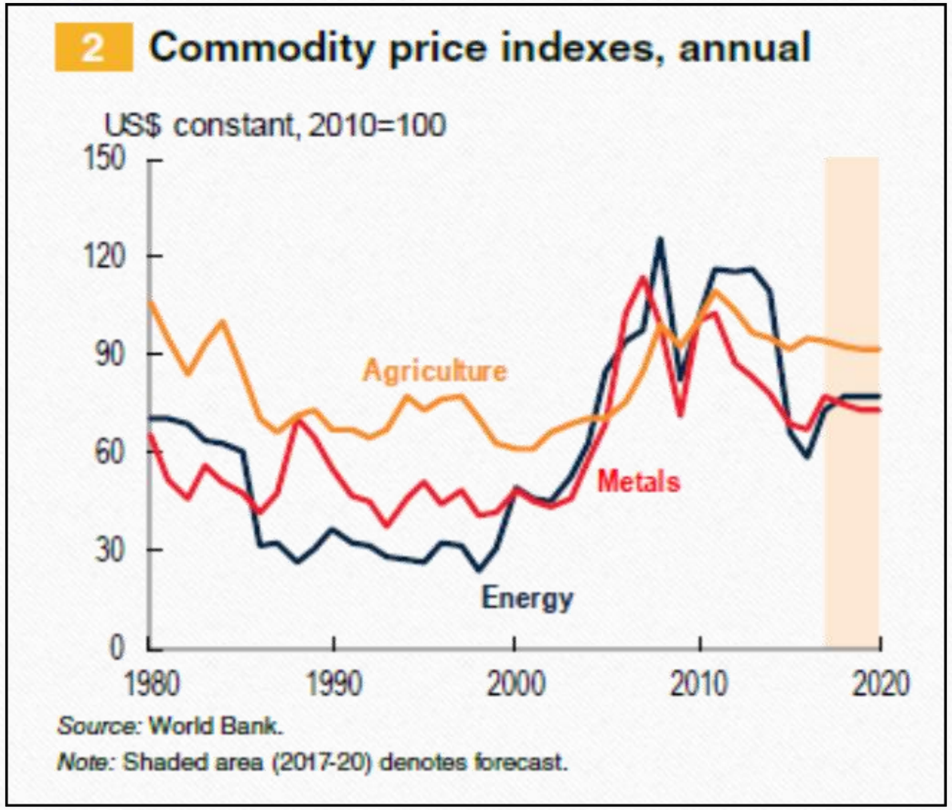
Adoption of wind renewable energy production



Source IEA (2017)

Is innovation driving adoption? Or is it increasing fuel prices?





Introduction

Why is the adoption of renewable energies important?

- Research question: Is innovation determining the adoption of renewable energies?
- Approach:
  - Use reduced form input demand function derived from classical profit maximization problem
  - Demand for renewable energy depends on price of electricity, cost per KW from solar or wind, price of fuel (with and without taxes), 1990-2015
  - But because of the commodity price super cycle, metal inputs for solar or wind capital goods are correlated with price of fuel, and therefore the cost per KW from solar or wind is also correlated with the price of fuel
  - We develop a two stage approach to isolate the effect of innovation on adoption:
  - 1) Renewable energy innovation: cost per KW from solar or wind depends on stock of knowledge for solar or wind (patents)
  - 2) Demand for renewable energy: Demand for renewable energy depends on predicted cost per KW from solar or wind based on technological change only and price of fuel

Introduction

Why is the adoption of renewable energies important?

- Results:
  - Innovation induces renewable energy adoption
  - Fuel price and fuel taxes are either non-significant or influence at a smaller scale adoption
  - We should expect adoption to continue even if fuel prices decline, and strengthen when fuel prices increase

- Discussion
  - Broad evidence that induced technological change is observed, including energy markets
  - Evidence of induced technological change in renewable energy markets just starting to stack up: Fuel prices and taxes induced technological change in renewables energy (Aghion et al 2012; Noailly and Smeets 2015; Calel and Dechezleprêtre 2016)
  - But we did not know if innovation (renewable energy cost reduction) led to adoption of renewable energy.
  - And indeed, we find evidence that technical change led to renewable energy production cost reduction and induced its adoption

- Further research
  - What is driving technological change: technological opportunity or fuel prices?

Introduction

Why is the adoption of renewable energies important?

- Pollution
  - Between 1960-2010 the CO_2 (kt) emissions increased 282% (Nasa, 2018).
- Energy production efficiency
  - Efficiency of solar panels to convert energy into electrical power was 6% in 1970, while nowadays it is 32% (NREL, 2018).
- Climate change
  - The rise of global temperature negatively impacts biodiversity, ecosystems, the sea level, among others (IPPC, 2018).
- Nonrenewable natural resource exploitation
  - Between 2006-2015 oil, coal and gas production has increased 11%, 22% and 23% respectively (British Petroleum, 2018).
- Energy consumption preferences
  - Between 1990-2014 the world's energy consumption mean of renewable energies increased 10.5% (World Bank, 2018)

Structure

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Data

Sources

- Energy generation:
  - Electricity and heat generation database from the IEA (2017)
- Resource Factor Endowment Distributions:
  - The Global Solar Atlas (2017).
  - The IRENA Global Atlas for Renewable Energy (2017).
- Energy prices:
  - **Electricity output prices:** Energy Prices and Taxes database of the IEA (2017).
  - **Fossil fuel prices:** Energy Prices and Taxes database of the IEA (2017).
  - **Solar PV module prices:** Berkley Electricity Markets & Policy Group (2017; Galen and Darghouth, 2016).
  - **Wind turbines prices:** Berkley Electricity Markets & Policy Group (2017; Wiser and Bolinger, 2017).
- Fuel taxes:
  - Energy Prices and Taxes database of the IEA (2017).
- Knowledge stocks and spillovers:
  - World Intellectual Property Organization (2017).

Data

Cost per KW from solar or wind energy

Cost of producing renewable energy

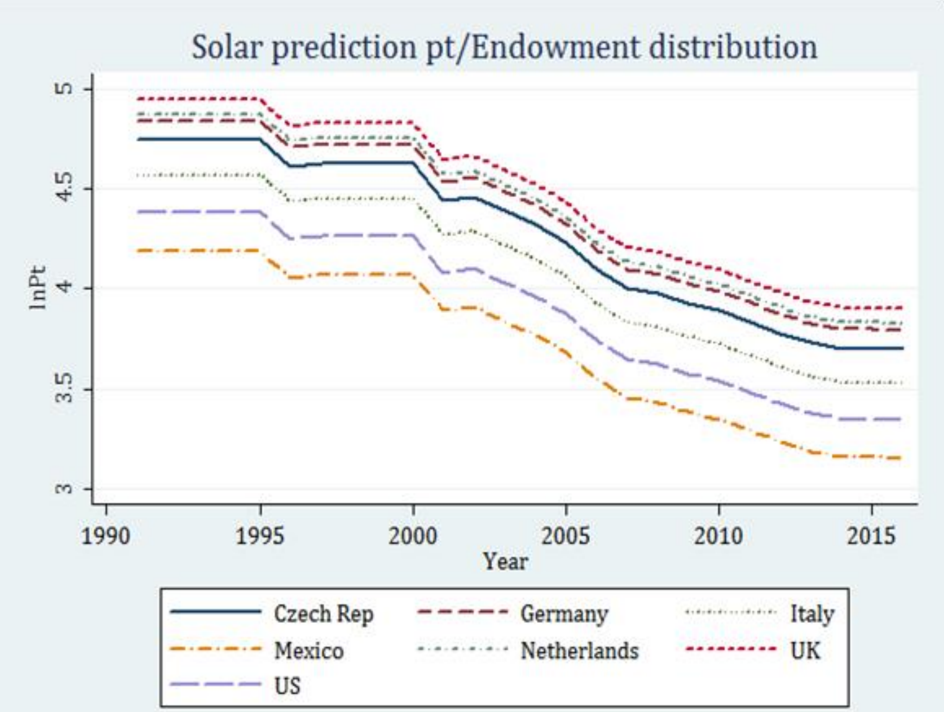
- Cost of capital goods in efficiency terms = cost per KW from solar or wind
- Cost of renewable resource = 0
- But we have to account for differences across countries in availability of renewable resource
- US efficiency prices for solar PV modules and wind turbines by the relative resource availability of solar irradiance and wind speed.

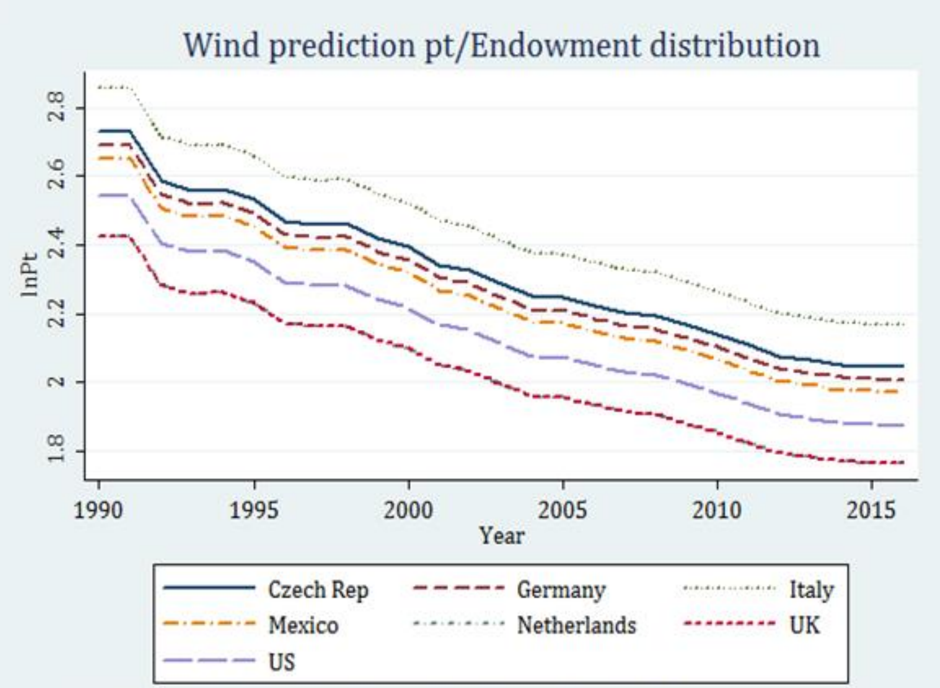
$$\hat{P}_{s_{i,t}} = \frac{\widehat{lnKP_{t,s}}}{Solar\ RRA._i}; \qquad \hat{P}_{w_{i,t}} = \frac{\widehat{lnKP_{t,w}}}{Wind\ RRA._i}$$

❖ Relative resource availability (RRA): $\frac{Wind\ Speed_i\ (\frac{m}{s})}{Max(Wind\ Speed(\frac{m}{s}))}; \frac{Solar\ Irradiance\ d_i\ (\frac{Kw}{m^2})}{Max(Solar\ Irradiance\ (\frac{Kw}{m^2}))}$

First Stage

Predicted cost per KW from solar or wind

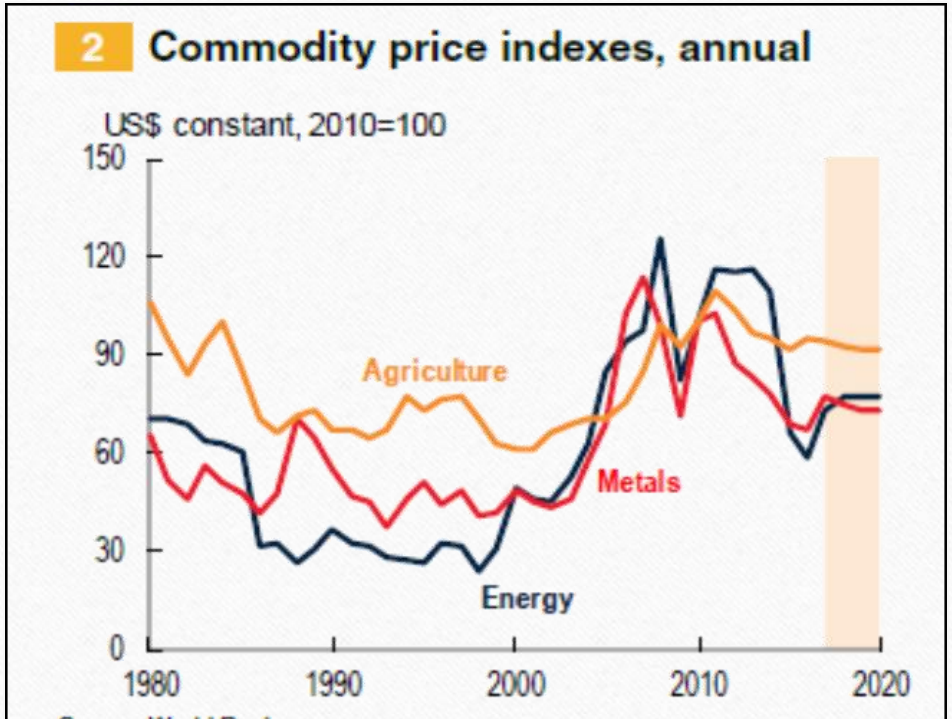




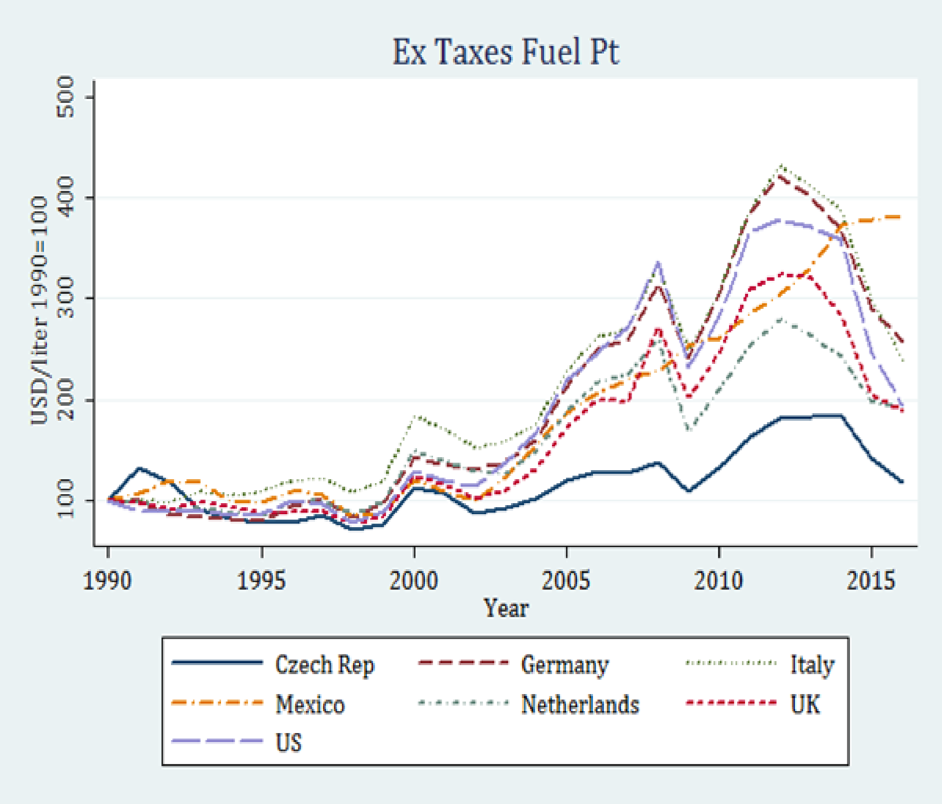
Uk and the Netherlands share the same trajectory because both have the same wind speed distribution.

Data

Commodities Super-Cycle

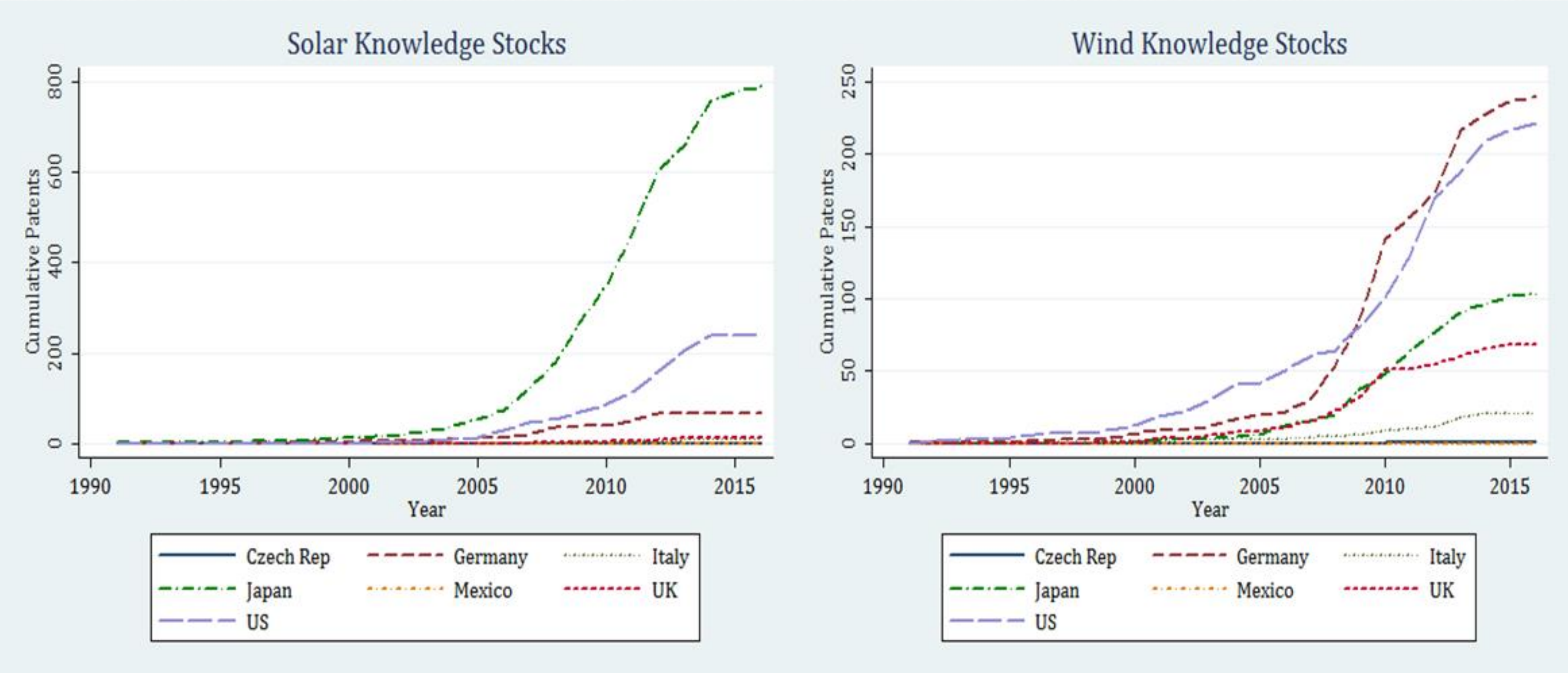


Source: World Bank.
Note: Shaded area (2017-20) denotes forecast.



Data

Knowledge Stocks



Data from the World Intellectual Property Rights (2017)

- Knowledge stocks calculation: $KS_{it} = (1 - \delta) * KS_{it-1} + P_{it}$
- Where KS_{it} are the country's knowledge stocks, δ is the depreciation rate (15%) of knowledge and P_{it} are the current period patents (Aghion et al, 2012; Hall and Mairesse, 1995; Park and Park 2006; Bointner; 2014) .

Structure

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First Stage

Time series OLS

VARIABLES	(1) Solar Total Installation Efficiency Pt	(2) Wind Total Installation Efficiency Pt
Lag ln(US Solar Knowledge Stocks)	-0.1930***	
	(0.039)	
Lag ln(Metals and Minerals Commodity pt)	0.1197	0.4765***
	(0.145)	(0.053)
Lag ln(US Wind Knowledge Stocks)		-0.1395***
		(0.020)
Constant	4.1205***	2.2121***
	(0.618)	(0.217)
Observations	24	25
R-squared	0.871	0.635
Country	US	US

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- All coefficients have expected signs.
- Biased technological change has been significant to reduce the efficiency prices of solar PV modules and wind turbines (less important).

Second Stage

Solar Energy Adoption

VARIABLES	(1) Solar Electricity % of Total	(2) Solar Electricity % of Total	(3) Solar Electricity % of Total	(4) Solar Electricity % of Total	(5) Solar Electricity % of Total	(6) Solar Electricity % of Total	(7) Solar Electricity % of Total	(8) Solar Electricity % of Total
lnspt	-0.5101***	-0.5026***	-0.4446***		-0.4595**			
	(0.084)	(0.072)	(0.091)		(0.173)			
lneindex22		0.2379	0.3285	0.4389*	0.3261		0.1223	0.1325
		(0.229)	(0.250)	(0.225)	(0.259)		(0.188)	(0.183)
lnavg33			0.1302	0.1658*	0.1308		-0.0930	-0.0353
			(0.131)	(0.092)	(0.128)		(0.091)	(0.079)
lnavg11				0.2988***	-0.0126			-0.1687**
				(0.055)	(0.108)			(0.062)
L.lnspt						-0.4968***		
						(0.090)		
L.lneindex22						0.2966		
						(0.242)		
L.lnavg33						0.1370		
						(0.132)		
lnspt2							-0.8109***	-0.9713***
							(0.127)	(0.137)
Constant	2.3279***	1.1758	-0.1447	-4.2328***	-0.0097	0.2131	4.0146***	5.2957***
	(0.362)	(1.053)	(1.857)	(1.341)	(2.622)	(1.748)	(1.303)	(1.289)
Observations	826	726	651	678	651	624	678	678
R-squared	0.317	0.347	0.367	0.344	0.367	0.391	0.524	0.535
Number of unit_id	34	30	27	27	27	26	27	27
FE	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

- Evidence suggests that technological change is inducing solar energy adoption although fuel price decreases..
- Robustness checks in Columns 6, 7 and 8 suggest that (i) coefficients in Column 3 are robust, (ii) Columns 7 and 8 show the effects of the endogeneity implied by the effect of the commodity super cycle (metals and mineral prices effect).

lnspt	Prediction of solar PV pt/endowment dist.
lneindex22	Electricity output pt
lnavg33	Fuel taxes
lnavg11	Fuel pt
lnspt2	Original solar PV pt/endowment dist.

Second Stage

Wind Energy Adoption

VARIABLES	(1) Wind Electricity % of Total	(2) Wind Electricity % of Total	(3) Wind Electricity % of Total	(4) Wind Electricity % of Total	(5) Wind Electricity % of Total	(6) Wind Electricity % of Total	(7) Wind Electricity % of Total	(8) Wind Electricity % of Total
lnwpt	-2.2656***	-2.3011***	-2.3906***		-1.0330***			
	(0.276)	(0.320)	(0.363)		(0.333)			
lneindex22		0.4005	0.3279	0.2070	0.1572		0.6908	0.2343
		(0.331)	(0.362)	(0.382)	(0.377)		(0.469)	(0.398)
lnavg33			0.0952	0.3112***	0.0638		1.3564***	0.2704**
			(0.146)	(0.084)	(0.126)		(0.280)	(0.098)
lnavg11				0.9689***	0.7066***			0.9864***
				(0.129)	(0.118)			(0.127)
L.lnwpt						-2.5463***		
						(0.392)		
L.lneindex22						0.2456		
						(0.378)		
L.lnavg33						0.0534		
						(0.145)		
lnwpt2							0.3755**	-0.0981
							(0.136)	(0.111)
Constant	5.6691***	3.9502*	4.0216*	-6.7635***	-1.6189	5.0253**	-11.2236***	-6.3279***
	(0.624)	(1.945)	(2.089)	(1.453)	(1.454)	(2.297)	(1.507)	(1.260)
Observations	884	780	702	702	702	675	702	702
R-squared	0.541	0.586	0.623	0.664	0.680	0.635	0.467	0.664
Number of unit_id	34	30	27	27	27	27	27	27
FE	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- Evidence suggests that technological change is inducing wind energy adoption although fuel price decreases.
- Robustness checks in Columns 6, 7 and 8 suggest that (i) coefficients in Column 3 are robust, (ii) Columns 7 and 8 show the effects of the endogeneity implied by the effect of the commodity super cycle (metals and mineral prices effect).

lnwpt	Prediction of wind turbine pt/endowment dist.
lneindex22	Electricity output pt
lnavg33	Fuel taxes
lnavg11	Fuel pt
lnwpt2	Original wind turbines pt/endowment dist.

Structure

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Conclusions

- Principal Results
  - Evidence suggests that innovation induces renewable energy adoption of solar and wind energies.
  - Results are consistent with patterns of adoption observed in the last 10 years.
  - We should expect adoption to continue even if fuel prices decline, and strengthen when fuel prices increase.
  - Finally, this study fills a gap in the literature studying if innovation is inducing the adoption of solar and wind energies by using an input demand function.
- Further Research
  - What is driving technological change: technological opportunity or fuel prices?
  - We suggest a three stage regression analysis:
    - First stage: $\widehat{Patents}_{t,R}(Art_{t,R}, Cit_{t,R}, Op_{t,R}, Pp_{t,R})$
    - Second stage: $lnKP_{t,R} = \alpha_0 + \alpha_1 ln\widehat{KS}_{t,R} + \alpha_2 lnMtls_t + \varepsilon_t$
    - Third stage: $lnR_{i,t} = \alpha_0 + \beta_1 lnP_{E_{i,t}} - \beta_2 ln\widehat{KP}_{R_{i,t}} + \beta_3\, lnP_{f_{i,t}} + \beta_4 lnT_{f_{i,t}} + u_{it}$

Where:

- $Art_{t,R}, Cit_{t,R}, Op_{t,R}, Pp_{t,R}$ mean articles, citations, other patents, past patents, respectively.
- $R\epsilon(Solar,\ Wind)$
- $\widehat{KS}$ are the US knowledge stocks calculated with the patents prediction estimated in the first stage.

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Theoretical Framework

What we know about the determinants of renewable energies adoption

- The reduced form model: Input demand function
  - Electricity generators choose from the mix of energy sources the quantity of electricity to be produced and sell to final consumers.
  - Different energy sources are inputs for electricity production.
  - The rate of adoption of different energy sources is determined by the demand of electricity generators for each type of energy.
  - As a result, the decision to adopt renewable energies can be modeled as an input demand function derived from classic profit maximization (Uri, 1978; Bopp & Costello, 1990).

$$max\ \Pi(R, F) = p_E R^{\alpha} F^{\beta} - p_R R - p_f F \qquad (1)$$

❖ Where $R\epsilon(Solar,\ Wind), F\epsilon(fuel\ energies, fuel\ taxes), E{:}\ Elecricity\ output.$

Theoretical Framework

Reduced form model

- The competitive assumption is that the price of the energy (p) is not a function of R and F.
- A classic profit maximization model, where electricity is the final good, renewable energies (R) and fossil energies (F) are inputs of production and behave like substitutes.
- Therefore, the input demand function for renewable energies should be a function of the electricity prices and the energy input prices: $R^*(p_E, p_{R(p_s,p_w)}, p_{f(p,\tau)})$.

Theoretical Framework

Model

Maximization Problem

- $max\ \Pi(R,F) = p_E R^{\alpha} F^{\beta} - p_R R - p_f F$

Input Demand Function for Renewable Energies

- $\mathrm{lnRW}(P_E, P_R, P_f) = \underbrace{-\frac{\alpha}{\alpha+\beta-1} ln\alpha - \frac{1-\alpha}{\alpha+\beta-1} ln\beta}_{\beta_0} + \underbrace{\frac{1}{1-\alpha-\beta}}_{\beta_1} lnP_E + \underbrace{\frac{1-\alpha}{\alpha+\beta-1}}_{\beta_2} (lnP_R) + \underbrace{\frac{\alpha}{\alpha+\beta-1}}_{\beta_3} (lnP_f)$

The Reduced form Model

- $\mathrm{lnRW}(P_E, P_R, P_f) = \beta_0 + \beta_1 lnP_E - \beta_2 lnP_{R(p_s,p_w)} + \beta_3\ lnP_{f(p,\tau)}$

Theoretical Framework

What do we know about the determinants of renewable energies adoption?

- Factor endowments, biased technical change and innovation:
  - Solar photovoltaics (PV) and wind turbines industries have been characterized by a large market expansion, rising demand, excess inventory, declining government support, and a significant price reduction, during the past decade (Sawind, 2012; Sawin, Sverrisson, & Rickerson, 2015; Sawin, Seyboth, & Sverrisson, 2017; Mints, 2016).
  - Renewable energy resources like solar irradiance & wind speed are non tradable goods, and their endowment are heterogenous across countries.
  - Differences in factor endowment and in capital goods prices are key mechanisms that induce biased technological change which may be determining the rate of adoption of these technologies (Hicks, 1932; Habakkuk, 1962; Acemoglu, 2002, 2012; Zuleta, 2008).
  - Knowledge stocks and spillovers facilitates technical contributions on a new technology improving its quality and reducing its cost (Rosenberg, 1972; Popp et al, 2010; Hall & Khan, 2003; Aghion, 2012; Acemoglu; 2012; Dechezleprêtre, 2014; Pargal & Wheeler, 1996; Poop, 2002, 2006;. Rosenberg, 1972; Hall & Khan, 2003).

Theoretical Framework

What we know about the determinants of renewable energies adoption

- Policy instruments and lobby:
  - The rate of innovation and adoption of a technology can be positively or negatively affected by political decisions influenced by lobbies (Comin and Hobijn, 2010).
  - Environmental policies have induced clean patenting & innovation. In particular, optimal policy in renewable energy adoption involves both "carbon taxes" and research subsidies (Acemoglu, 2012; Peretto, 2007; Newell et al, 1999; Aghion et al 2012; Calel & Dechezleprêtre, 2014).
  - The interaction between political institutions and interest groups (lobbies) will produce a political equilibrium that will accelerate or slow down the adoption of a these technologies (Hall & Khan, 2003; Comin and Hobijn, 2010; Heiniz & Zelner, 2006; Pargal & Wheeler, 1996).
  - Government interventions in technology markets can incentivize or block the adoption of a technology by changing the relative cost of production between competing technologies (Comin and Hobijn, 2010; Acemoglu et al, 2012; Peretto, 2009; Pargal & Wheeler, 1996; Aghion et al, 2012; Heiniz & Zelner, 2006; Duran, 2013; Duran and Bucheli, 2017; Newell et al, 1999; Bointner, 2014; Calel & Dechezleprêtre, 2014).

Data

Dependent Variable Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Full sample					
Wind Energy as % of total	918	2.00	4.76	0.00	48.82
Solar Energy as % of total	893	0.34	1.05	0.00	8.11
Fossil Fuels Energy as % of total	909	55.07	30.74	0.01	100.00
1990					
Wind Energy as % of total	34	0.08	0.40	0.00	2.35
Solar Energy as % of total	34	0.00	0.00	0.00	0.00
Fossil Fuels Energy as % of total	35	56.02	32.24	0.07	100.00
2015					
Wind Energy as % of total	34	7.07	9.44	0.01	48.82
Solar Energy as % of total	33	1.88	2.10	0.00	8.11
Fossil Fuels Energy as % of total	34	48.33	29.19	0.02	97.85

Data from the International Energy Agency (2017)

- Italy is leading the adoption of solar energy.
- Denmark leads the adoption of wind energy.
- Adoption heterogeneity of both technologies is important across countries. Solar cv=312%; wind cv=237%.
- Adoption rates have increased more than 2 orders of magnitude during the period.

Data

Independent Variables Descriptive Statistics

Variables	Obs	Mean	Std. Dev	Min	Max	p25	p50	p75
Electricity Output Prices USD Index 1990=100	780	109.20	29.65	56.01	271.99	91.10	102.32	120.39
Average solar irradiance (Kw/m^2)	910	1259.39	397.99	225.00	2154.50	1022.00	1168.00	1533.50
Average Wind speed (m/s)	910	6.44	1.33	3.75	9.00	5.50	7.00	7.50
Average solar irradiance Distribution	910	0.58	0.18	0.10	1.00	0.47	0.54	0.71
Average Wind speed Distribution	910	0.72	0.15	0.42	1.00	0.61	0.78	0.83
Average fossil fuels USD PPP/liter 1990=100	702	170.57	89.35	45.41	445.03	99.68	136.32	232.88
Average fuels taxes USD PPP/liter 1990=100	702	193.49	107.18	49.45	713.93	119.03	160.21	235.89
Private Solar Knowledge Stock	875	8.28	55.03	0.00	777.65	0.00	0.00	0.00
Private Wind Knowledge Stock	875	7.04	25.10	0.00	236.25	0.00	0.00	1.85
Public Solar Spillover Stock	875	281.58	407.24	0.00	1262.25	9.65	44.45	430.55
Public Wind Spillover Stock	875	239.40	306.72	0.00	952.25	14.45	82.05	374.35

Data from: the International Energy Agency (2017), the World Bank (2017), the Global Solar Atlas (2017), the Global Atlas for Renewable Energy (2017), the Electricity Market & Policy Group (2017) and the World Intellectual Property Rights (2017).

- Factor endowment of solar irradiance (cv=32%) and wind speed (cv=20%) is heterogenous across countries.
- Fuel prices increased significantly more than electricity prices.
- Differentials in fuel taxes are generating diverse incentives to adopt renewable energies across countries (cv=55%).
- However, the 75% of the fuel taxes distribution is only 21% above the mean.
- Average knowledge stocks increased around 4 times during the period (in 2015 solar=36; wind=27).
- The US and Japan have the lion's share innovative activity for solar panels while Germany and the US are the major knowledge producers for wind turbines.
- Overall innovation activities in both technologies are very significant. Spillovers are almost two orders of magnitude higher than knowledge stocks.

Data

US Variables Descriptive Statistics

Variables	Obs	Mean	Std. Dev	Min	Max	p25	p50	p75
Solar panel efficiency prices USD/Kw 1990=100	26	76.20	21.94	32.14	100.00	66.66	84.06	94.05
Wind turbines efficiency price USD/Kw 1990=100	26	62.84	13.99	43.62	100.00	52.15	60.07	73.56
Metals & minerals commodity index USD 1990=100	26	144.74	77.77	71.08	309.59	82.24	101.21	221.53
Private Solar Knowledge Stock	25	51.21	78.23	0.00	238.20	0.85	5.40	70.70
Private Wind Knowledge Stock	25	59.11	69.85	0.00	216.70	6.80	30.25	80.75

Data from: the Electricity Market & Policy Group (2017) and the World Intellectual Property Rights (2017).

- Solar PV modules and wind turbines efficiency prices experienced reductions of 57% and 68% respectively.
- The metals and minerals commodity prices grew 309% because of the commodities super-cycle.
- The US solar and wind knowledge stocks increased 3 orders of magnitude during the period studied.

Data

Issues

- Lack of data:
  - Solar PV modules and wind turbines are only for the US.
  - Metals and minerals prices are not for country-level.
  - Silicon prices would be a more accurate input to explain changes in solar PV modules prices.
  - Solar and wind subsidies may be important to understand the effect of induced technological change over solar and wind technologies prices.
- Endogeneity:
  - Commodity prices are highly correlated between 2000 and 2010 because of a commodity prices super-cycle.
  - Therefore, the input prices (metals and minerals, and silicon) for solar PV modules and wind turbines are highly correlated with fuel prices.

Empirical Strategy

Basic Model

- To examine if biased technological change, policy instruments and fuel prices are determining the adoption of solar and wind energies, I use a two-stage regression analysis.
- In the first stage, I use a OLS time series regression to test if the total installation efficiency prices of solar panels and wind turbines are affected by technological change and their input prices.
- To estimate the effect of biased technological change in the second stage, I calculate the predictions of these regressions using the coefficient that measures the effect of technological change and avoid the effect of the input prices.
- In the second stage, I use a fixed effect model to test if the variables implied in the input demand function for renewable energies are significant to induce the adoption of solar and wind energies:

- Energy prices.
- Fuel taxes.
- Electricity output prices.

Empirical Strategy

Addressing the Specification Problems

Problems	Solutions
Spurious relationship →	Theory & Cointegration test
Endogeneity; Unobserved heterogeneity }	Panel data and lag variables; Robust standard errors

Empirical Strategy

First Stage

- In equation (6) and (7), t is the time index, KP_s and KP_w are the US solar and wind total installation efficiency prices, KS_s and KS_w are the US knowledge stocks of solar and wind energies, $Mtls$ are the metals and minerals commodity prices, ε is the error term, α_0 is the constant of the regression and $\alpha_{1,}$ $\alpha_{2,}$ are the variable coefficients.

$$lnKP_{t,s} = \alpha_0 + \alpha_1 lnKS_{t,s} + \alpha_2 lnMtls_t + \varepsilon_t \qquad (6)$$

$$lnKP_{t,w} = \alpha_0 + \alpha_1 lnKS_{t,w} + \alpha_2 lnMtls_t + \varepsilon_t \qquad (7)$$

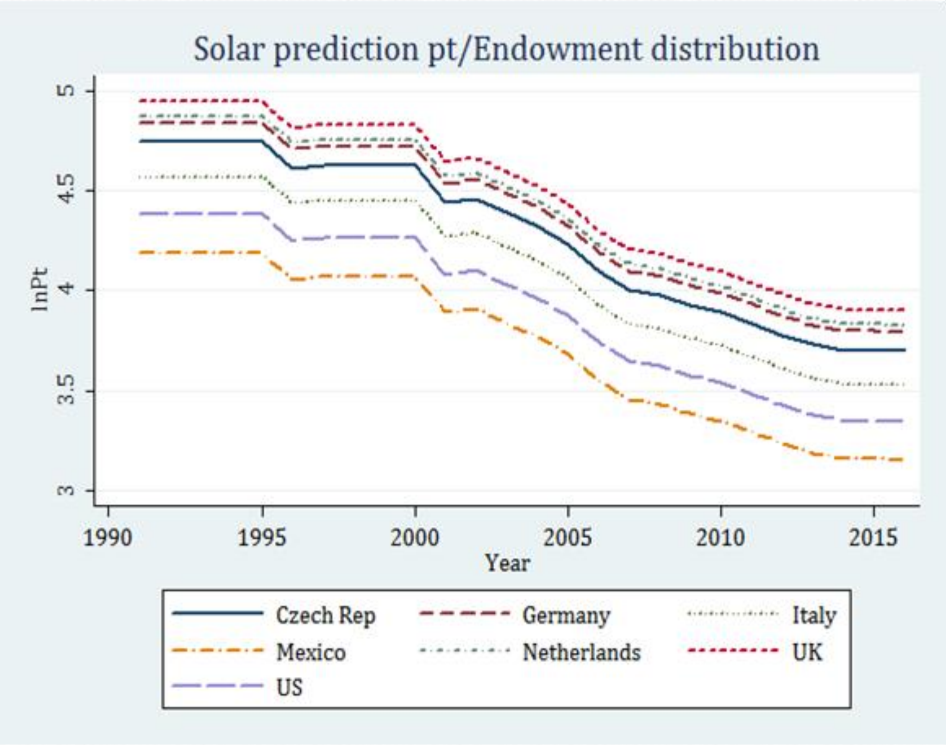
- To approximate for the cost heterogeneity implied by the factor endowment distribution across countries, I divide the technological predictions of the US efficiency prices for solar PV modules and wind turbines by the endowment of solar irradiance and wind speed.

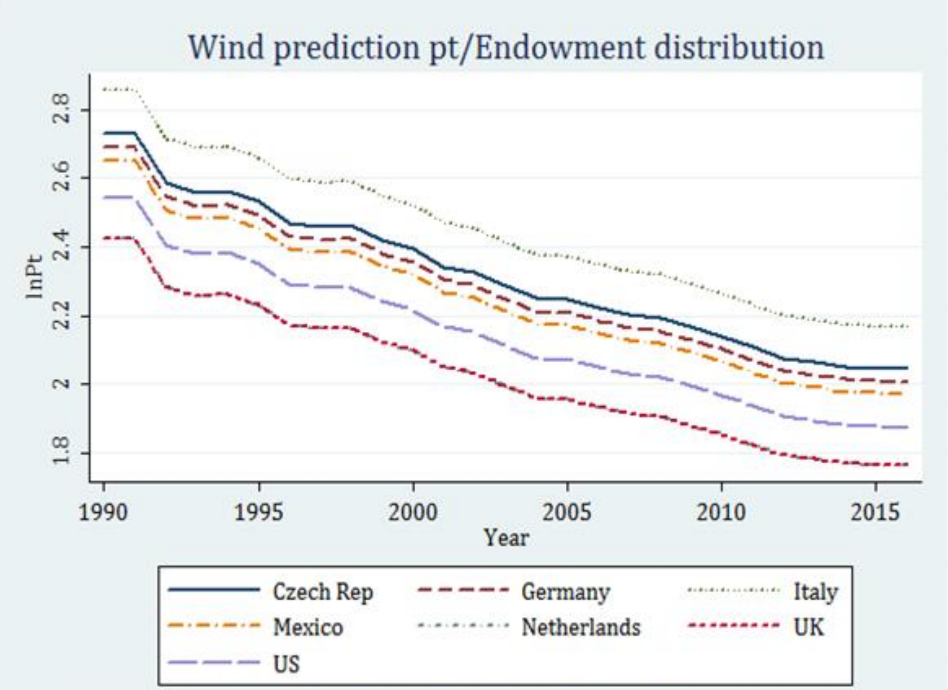
$$\hat{P}_{s_{i,t}} = \frac{\widehat{lnKP_{t,s}}}{Solar\ Irradiance\ Dist._i}; \qquad \hat{P}_{w_{i,t}} = \frac{\widehat{lnKP_{t,w}}}{Wind\ Speed\ Dist._i}$$

- where the resource distributions are: $\frac{Wind\ Speed_i\ (\frac{m}{s})}{Max(Wind\ Speed(\frac{m}{s}))}$; $\frac{Solar\ Irradiance\ d_i\ (\frac{Kw}{m^2})}{Max(Solar\ Irradiance\ (\frac{Kw}{m^2}))}$

Empirical Strategy

First Stage





Uk and the Netherlands share the same trajectory because both have the same wind speed distribution.

Empirical Strategy

Second Stage

- Using a fixed effects methodology I estimate the log of the input demand function for renewable energies, derived from a profit maximization of a Cobb-Douglas electricity production function.
- In Equations (7) and (8), i, t are the country-time indexes, RS and RW are the solar and wind electricity measure of adoption (electricity production shares), p_E is the electricity market price, p_s and p_w are the cost of solar and wind and energies, p_f and T_f are the fuel prices and taxes, α_i is the individual effect, $\beta_{1,..,4}$ are the variable coefficients and $u_{i,t}$ is the error term:

$$lnRS_{i,t} = \alpha_0 + \beta_1 lnP_{E_{i,t}} - \beta_2 ln\hat{P}_{s_{i,t}} + \beta_3\, lnP_{f_{i,t}} + \beta_4 lnT_{f_{i,t}} + u_{it} \qquad (7)$$

$$lnRW_{i,t} = \alpha_0 + \beta_1 lnP_{E_{i,t}} - \beta_2 ln\hat{P}_{w_{i,t}} + \beta_3\, lnP_{f_{i,t}} + \beta_4 lnT_{f_{i,t}} + u_{it} \qquad (8)$$

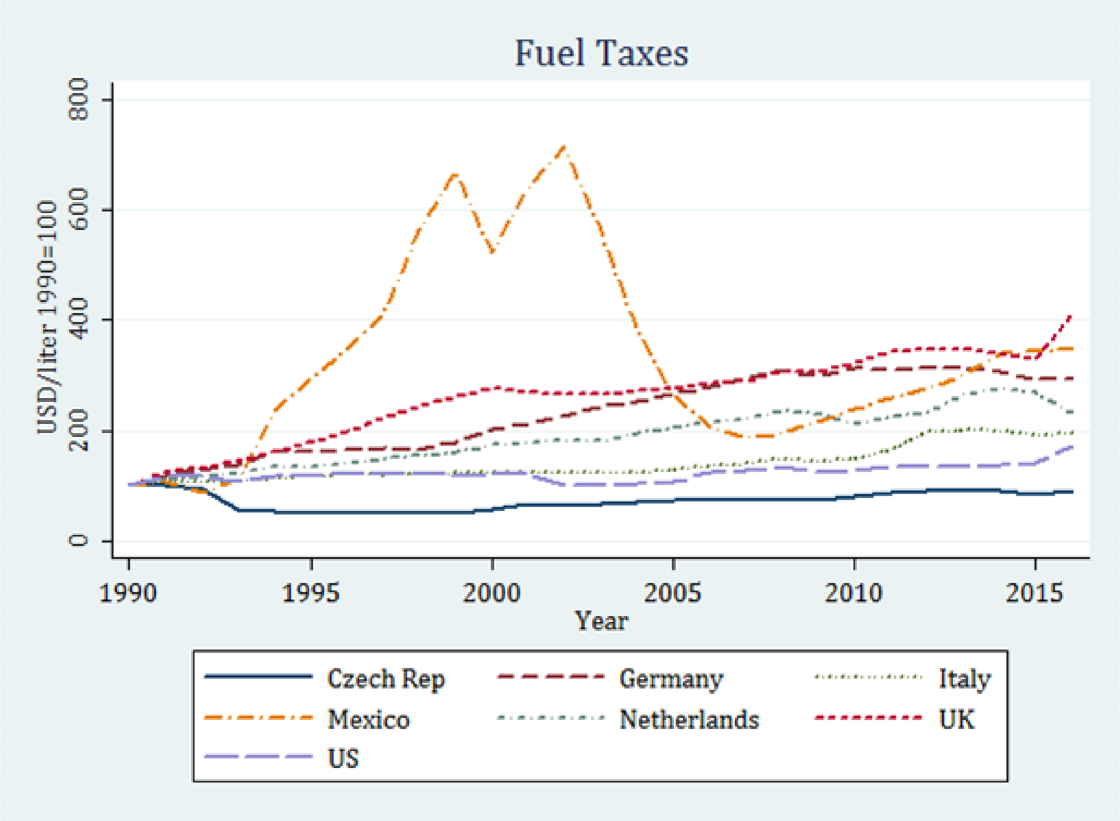
Empirical Strategy

Estimation Issues

- A three-stage regression analysis should be incorporated to study the determinants of technological innovation (technological opportunity) of solar PV module and wind turbines industries (Aghion et al, 2012; Calel & Dechezleprêtre, 2014).
- A dynamic panel estimation should be considered to control for possible endogeneity. The inclusion of lags of the dependent variable seems to provide an adequate characterization of many economic dynamic adjustment processes (Bun & Sarafidis, 2013).
- The substitutability between solar and wind energy production should to be better explored. Although evidence may indicate that both energy sources are substitutes, seasonal, location, diurnal and infrastructure complementarities may produce that wind and solar energies behave like complements (Wu et all, 2015; NREL, 2016).
- Finally, it seems that fuel prices are affecting the innovation process of solar PV modules and, consequently, generating a endogenous relation between fuel prices and solar energy prices. However, this effect is complex and difficult to identify because of the structure of the solar PV module industry (Sawin, J. L. et al, 2012; 2015; 2017) .

Data

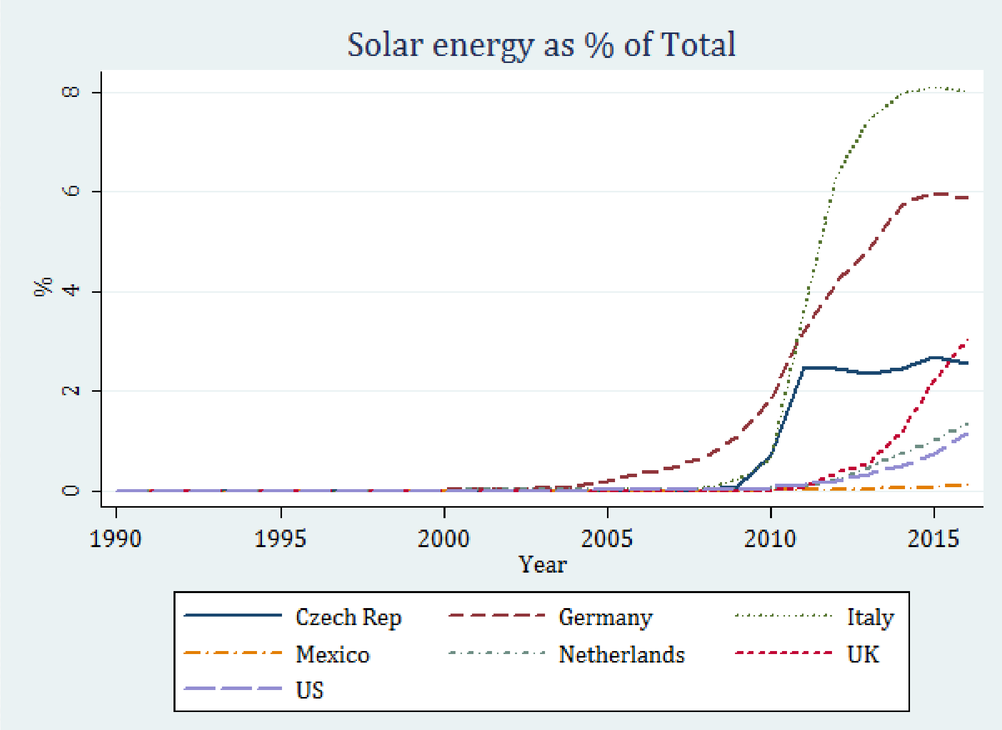
Fuel Taxes

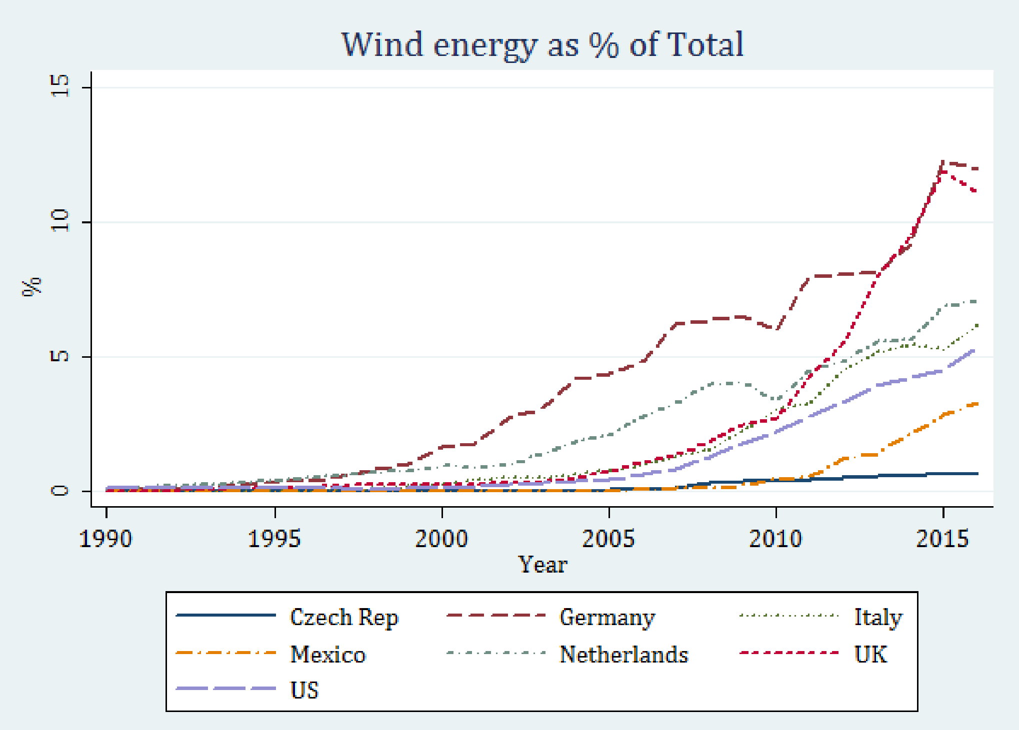


Source IEA (2017)

Data

Energy Production

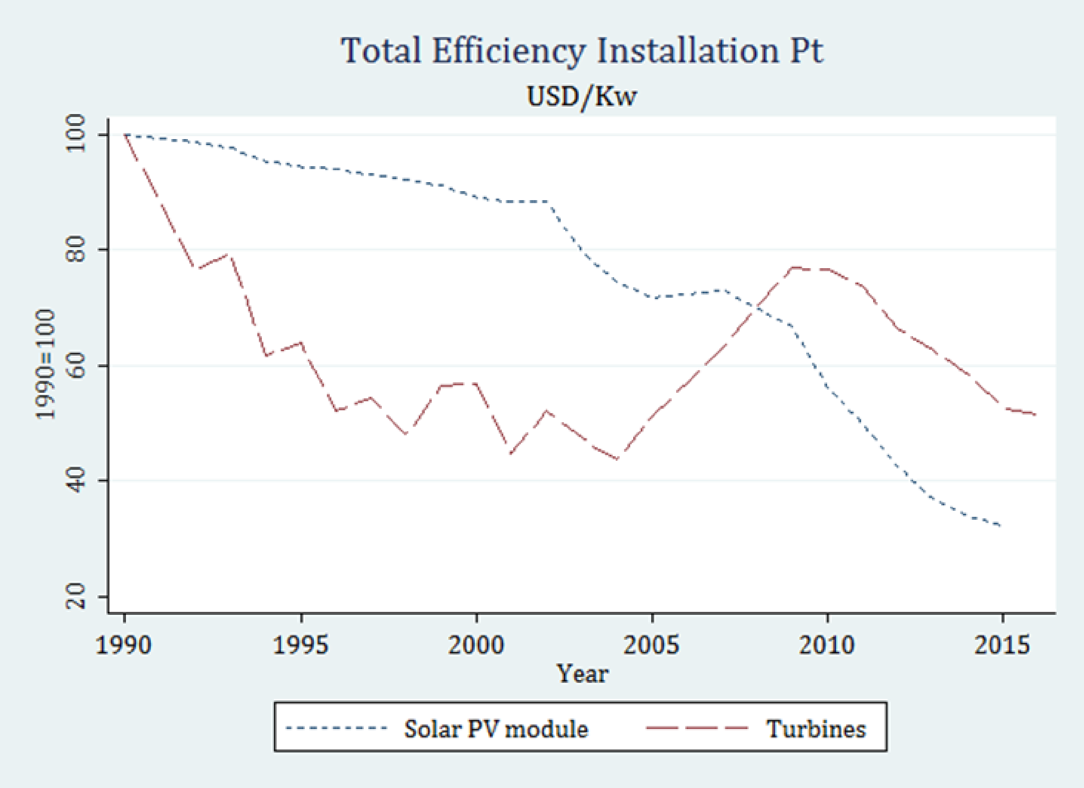




Source IEA (2017)

Data

Solar PV Modules and Wind Turbines Prices



Source: the Berkley Electricity & Policy Group (2017)

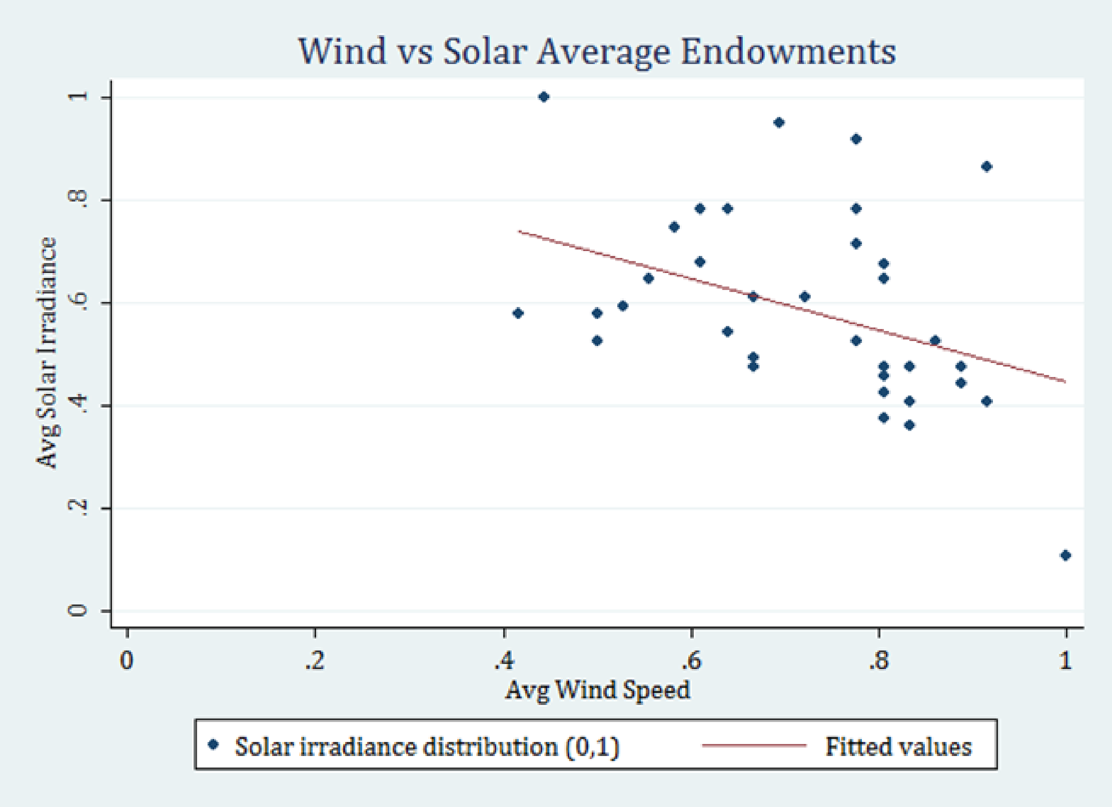
- I reconstruct the solar photovoltaic (PV) installation prices between 1990 and 1998 due to incomplete data.
- Using the wind and solar capital goods index from the BEA (2017), I predict the solar prices.
- Then, I compute the prediction growth rate and project only the missing years.

$$P_{t-1} = P_t * (1 - Prediction\ growth\ rate_t)$$

❖ OLS regression: $\beta_0 = 17737;\ \beta_1 = -105.9;\ R^2 = 0.89.$

Data

Resource Factor Endowments Relationship



Source: Global Solar Atlas (2017) and the IRENA Atlas for Renewable Energy (2017)

Second Stage

Principal Elasticities

Elasticities	Technological change	Fuel prices
Solar	-0.44	-
Wind	-2.39	-
Wind	-1.03	0.7

- An increase of 1% in the prediction of solar PV modules prices reduces the adoption of solar energy in 0,44%.
- An increase of 1% in the prediction of wind turbines prices, when fuel prices are not included, decreases the adoption of wind energy in 2,39%.
- A rise of 1% in the prediction of wind turbines prices, when fuel prices are included, decreases the adoption of wind energy in 1,03%, whereas an increase of 1% in fuel prices augments the adoption of wind energy in 0,7%.

Introduction

Why is the adoption of renewable energies important?

- Results:
  - Innovation induces renewable energy adoption
  - Fuel price and fuel taxes are either non-significant or influence at a smaller scale adoption
  - We should expect adoption to continue even if fuel prices decline, and strengthen when fuel prices increase
- Discussion
  - Broad evidence of induced technological change
  - Input prices and taxes induced technological change in renewables energy (Aghion et al 2012; Noailly and Smeets 2015; Calel and Dechezleprêtre 2016)
  - But we did not know if innovation (renewable energy cost reduction) led to adoption of renewable energy
  - We find evidence that technical change induced energy cost reduction and in fact led to adoption of renewable energy
- Further research
  - What is driving technological change: technological opportunity or fuel prices?

Conclusions

Further Research

- As mentioned before, understanding the determinants of technological innovation is essential to understand the process of adoption of solar and wind technologies for energy generation.

- Therefore, the next step of this analysis is to incorporate a tree stage regression analysis where we can explore the role of technological opportunity (articles, scientific publications, citations, other technologies patents and older patents) over the production of new patents for solar and wind technologies.

- Specifically what we suggest is:

  - First stage: $\widehat{Patents}_{t,R}(Art_{t,R}, Cit_{t,R}, Op_{t,R}, Pp_{t,R})$
  - Second stage: $lnKP_{t,R} = \alpha_0 + \alpha_1 ln\widehat{KS}_{t,R} + \alpha_2 lnMtls_t + \varepsilon_t$
  - Third stage: $lnR_{i,t} = \alpha_0 + \beta_1 lnP_{E_{i,t}} - \beta_2 ln\widehat{KP}_{R_{i,t}} + \beta_3\, lnP_{f_{i,t}} + \beta_4 lnT_{f_{i,t}} + u_{it}$

Where:

- $Art_{t,R}, Cit_{t,R}, Op_{t,R}, Pp_{t,R}$ mean articles, citations, other patents, past patents, respectively.
- $R\epsilon(Solar,\ Wind)$
- $\widehat{KS}$ are the US knowledge stocks calculated with the patents prediction estimated in the first stage.

i, t are country and time subindexes.