Laggard Sectors and Green Growth

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In this Paper - Overview

- Focus on the role of innovation policies (i.e. subsidies) in decoupling fossil fuels from economic growth;
- Global investment in low-carbon energy technologies was $286 billions in 2015, mostly targeting renewable electricity capacity with $265.8 billions (Bloomberg and UNEP 2016).
    - Yet, electricity is less than one third of total energy demand.
- In an economy with multiple and complementary energy demands (i.e. electricity, heating, transport):
    - is the distribution of low-carbon innovation across energy demands relevant for long-run decoupling?

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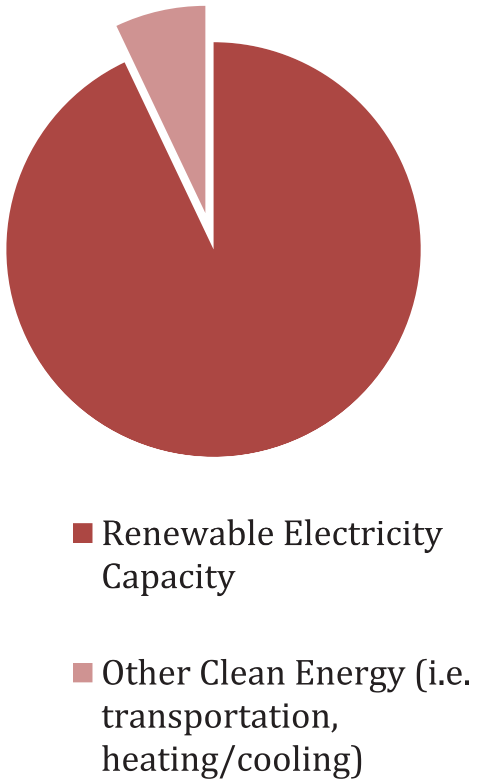
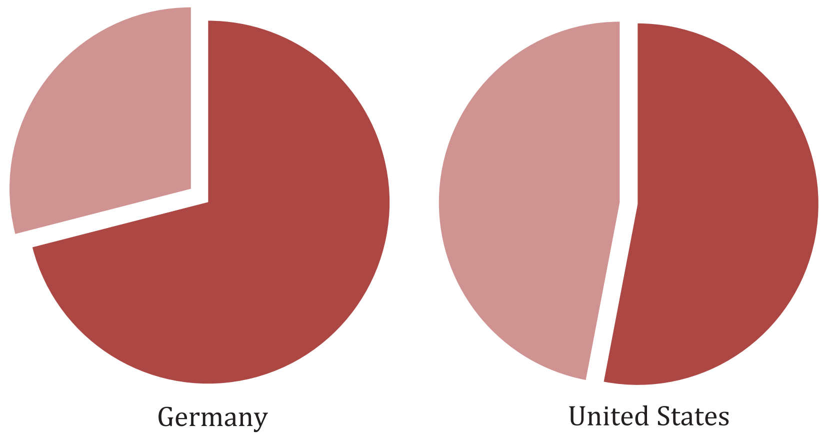
Low-Carbon Innovation and Policy: the Electricity Bias

Global low-carbon energy investment (2015)

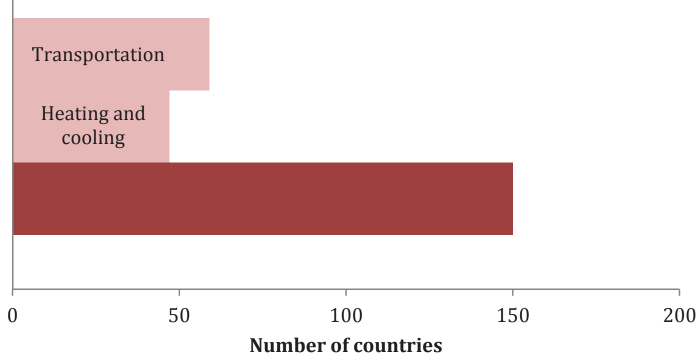


Sources: Bloomberg and UNEP (2016); OECD; Kieffer and Couture 2015.

Low-carbon energy R&D investment (2005-2013)



Sectoral renewable energy targets worldwide



Outline

The Model - Production

Aggregate energy-using output, Y, is divided into four sectors of energy-using activities, Y_j:
- *Electricity generation (ELE), Heating (HET), Transportation (TRA), Non-energy Use (NEU)*

Final output is produced with CES technology,

$$Y = \left[\sum_{j \in J} \pi_j Y_j^{\frac{\varepsilon - 1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon - 1}},$$

where $J = \{HET, ELE, TRA, NEU\}$. Each **sector** j uses clean inputs, $X_{C,j}$, and dirty inputs, $X_{D,j}$, with CES technology:

$$Y_j = \left[\mu_j X_{C,j}^{\frac{\sigma-1}{\sigma}} + (1 - \mu_j) X_{D,j}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

Working assumption: $\varepsilon < 1$ and $\sigma > 1$.

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The Model - Innovation

Innovation in **two fields of research**: low-carbon and fossil fuel energy.

Successful scientists obtain monopoly rights on manufacturing energy technologies $m_{h,jit}$.

Production of an energy input of type $h \in \{C, D\}$ is

$$X_{h,jt} = L_{h,jt}^{1-\alpha} \int_0^1 A_{h,it}^{\nu_{hj}(1-\alpha)} m_{h,jit}^{\alpha} di,$$

where $A_{h,it}$ is the productivity level of the intermediate good $m_{h,jit}$ applied to input h and α is a share parameter. **Technology wedges** ν_{hj} capture differences in sectoral absorptive capacity.

Decoupling

Decoupling rate

$$\hat{x}_t = -(\hat{X}_{D,t} - \hat{Y}_t)$$

Decoupling rate with uniform clean innovation policy:

$$\hat{x}_t = \bar{\sigma}\bar{\theta}_{C,t}\hat{A}_{C,t}$$

The aggregate elasticity of substitution between low-carbon and fossil fuel energy, $\bar{\sigma}$, is often assumed constant, but it is not.

Anatomy of the Macro Elasticity

Given $X_{h,t} = \sum_j X_{h,jt}$, the aggregate elasticity between clean and dirty inputs is:

$$\bar{\sigma}_t \equiv \frac{d \ln X_{C,t}/X_{D,t}}{d \ln (MP_{D,t}/MP_{C,t})} =$$

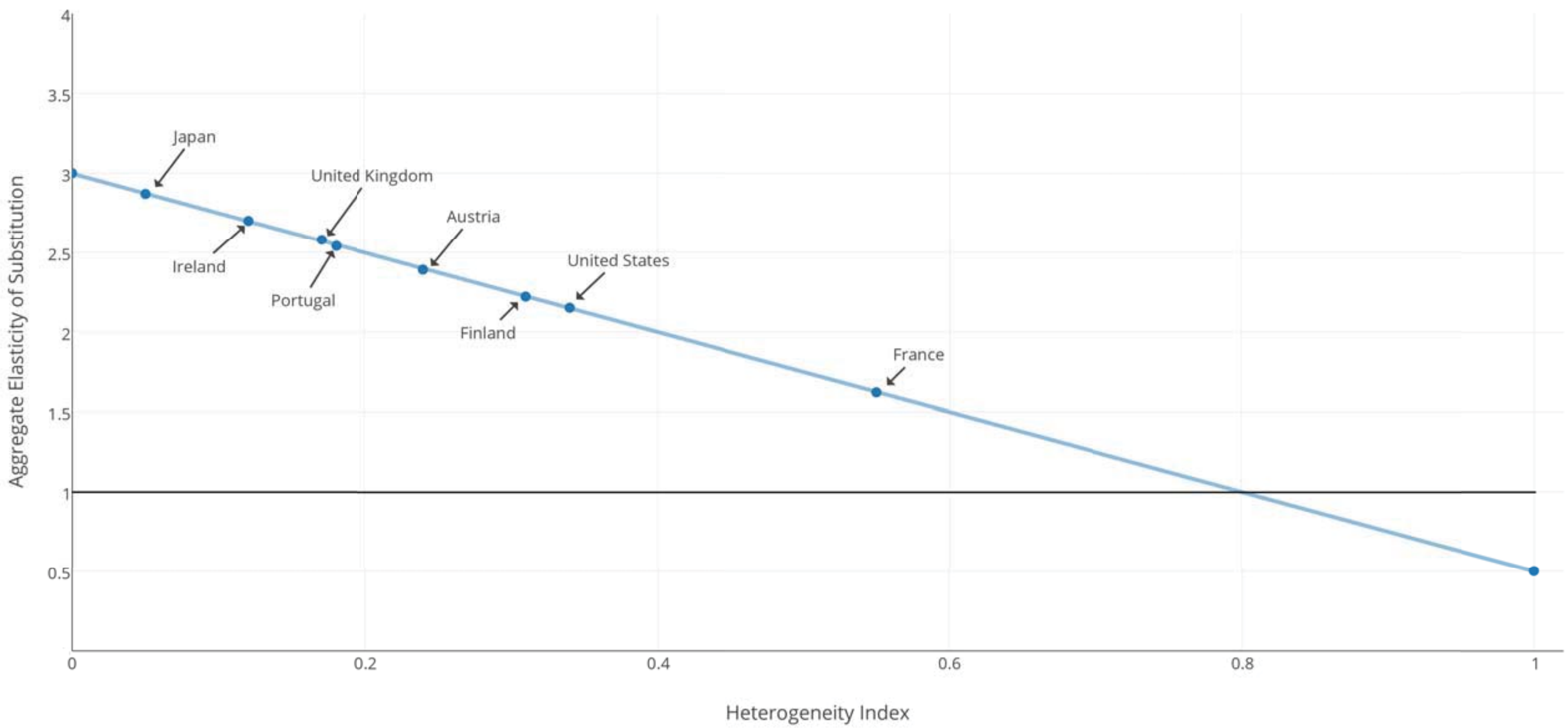
$$= (1 - \chi_t)\sigma + \chi_t \varepsilon.$$

where $\chi_t \equiv \sum_j \frac{(\theta_{jt} - \bar{\theta}_t)^2}{\bar{\theta}_t (1 - \bar{\theta}_t)} \omega_{jt}$ is the **heterogeneity index** (Oberfield and Raval 2015), measuring the polarization in the use of inputs across sectors.

Note:

- θ_{jt} is the clean cost share,
- $\bar{\theta}_t$ the economy-wide clean cost share
- ω_{jt} is the sectoral expenditure share.

Evidence on the Heterogeneity Index



The graph plots the **levels of χ_t observed in the data** for some countries, and the aggregate elasticity computed with $\sigma = 3$ and $\varepsilon = 0.5$. Empirical evidence on σ and ε is scarce and it would be of great importance for model calibration.

Estimation of $\bar{\sigma}$ - Novel Approach

Classic factor demand approach has limitations and data constraints do not allow to estimate neither a global elasticity $\bar{\sigma}$, nor σ.

Step 1. Innovation-side estimation of $\bar{\sigma}$
The average innovator on clean and fossil fuel intermediates faces the aggregate demand of energy inputs. From the model:

$$\frac{\Pi_{Ct}}{\Pi_{Dt}} = \frac{\bar{\theta}_t}{1-\bar{\theta}_t}, \text{ so that } \frac{\text{d } \ln \frac{\Pi_C}{\Pi_D}}{\text{d } \ln \frac{p_D}{p_C}} = \bar{\sigma} - 1. \qquad (*)$$

The relative profitability mirrors relative aggregate expenditures on low-carbon and fossil fuel energy.
Data: firm-level data on manufacturers of energy technologies (e.g. wind and gas turbines).

Step 2. Retrieve σ from $\bar{\sigma}$, χ and ε.

Result: $\bar{\sigma} = 1.53$, $\sigma = 1.71$.

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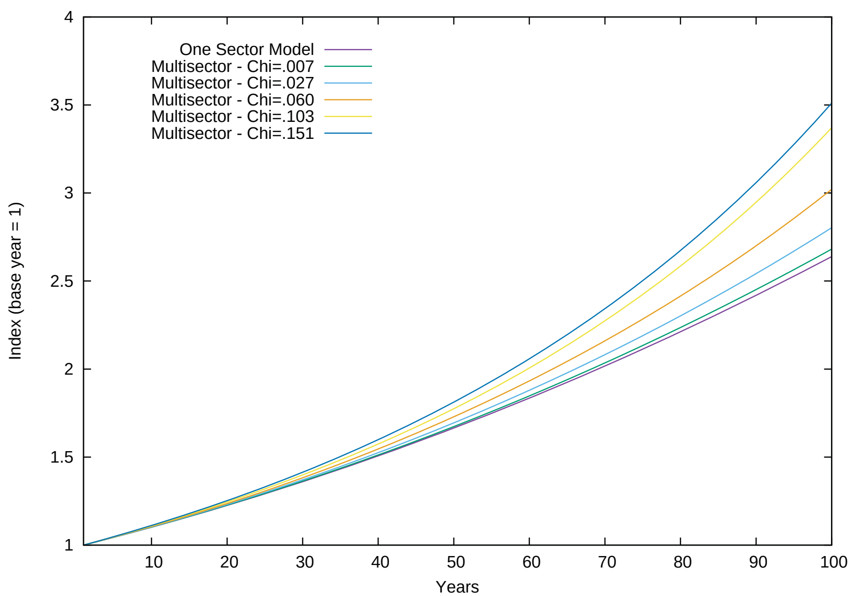
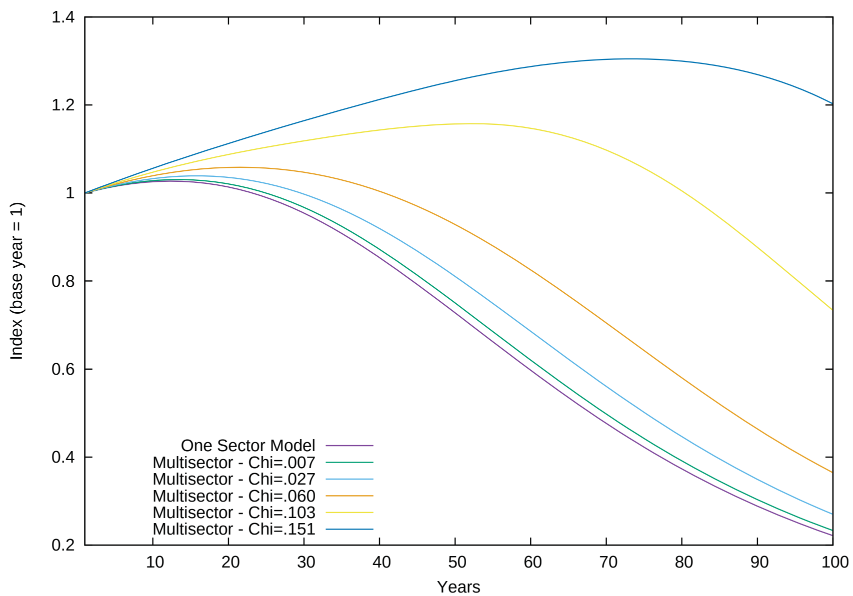
Uniform Clean Research Subsidy

Effect on X_D of the redirection of TC in a growing economy: comparison between levels of σ and χ.



Use of dirty inputs. Estimated $\sigma = 1.71$.



Use of dirty inputs. High $\sigma = 3$.

Conclusions

- Decoupling: not only the micro-level substitution matters, but also sectoral heterogeneity;
- New empirical strategy to estimate $\bar{\sigma}$: results send a pessimistic signal;
  - **energy-saving technology** is essential for the green growth transition;
- Intertemporal trade-off in sectoral innovation policies (in the paper): investing in leading energy technologies maximises short-term decoupling but reduces the aggregate elasticity of substitution;
- The diffusion of electric vehicles shifts energy demand towards electricity generation, reducing heterogeneity and making decoupling easier.

Thank you!