A SEMIPARAMETRIC ANALYSIS OF GREEN INVENTIONS AND ENVIRONMENTAL POLICIES

MASSIMILIANO MAZZANTI & ANTONIO MUSOLESI

Sustainability Environmental Economics and Dynamics Studies

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BACKGROUND RESEARCH AND FACTS

DE GRUYTER DOI 10.1515/snde-2012-0082 — Stud Nonlinear Dyn E 2013; aop

Antonio Musolesi* and Massimiliano Mazzanti

Nonlinearity, heterogeneity and unobserved effects in the carbon dioxide emissions-economic development relation for advanced countries

Abstract: We study long run carbon dioxide emissions-economic development relationships for advanced countries grouped in policy relevant groups: North America and Oceania, South Europe, North Europe. By relying on recent advances on Generalized Additive Mixed Models (GAMMs) and adopting interaction models, we handle simultaneously three main econometric issues, named here as *functional form bias, heterogeneity bias* and *omitted time related factors bias*, which have been proved to be relevant but have been addressed separately in previous papers. The model incorporates nonlinear effects, eventually heterogeneous across countries, for both income and time. We also handle serial correlation by using autoregressive moving average (ARMA) processes. We find that country-specific time related factors weight more than income in driving the northern EU Environmental Kuznets. Overall, the countries differ more on their carbon-time relation than on the carbon-income relation which is in almost all cases monotonic positive. Once serial correlation and (heterogeneous) time effects have been accounted for, only three Scandinavian countries – Denmark, Finland and Sweden – present some threshold effect on the CO_2-development relation.

Keywords: environmental Kuznets curve; generalized additive mixed models; interaction models; semiparametric models.

JEL classification: C14, C23, Q53.

Econ Polit
DOI 10.1007/s40888-017-0069-z

The effect of Rio Convention and other structural breaks on long-run economic development-CO_2 relationships

Massimiliano Mazzanti[1] · **Antonio Musolesi**[1]

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Abstract This paper assesses the effect of the 1992 United Nations Rio Convention on Environment and Development and other unknown structural time breaks on the long-run carbon dioxide—economic development relationship for different groups of advanced countries. By taking into account the possible size distortion of standard unit roots tests and allowing nonlinearities in the trend function, we provide evidence suggesting that the time-series are nonlinear trend stationary. From this result, we then develop our analysis without moving to cointegration or first-differencing, and using an interrupted time-series approach, we identify three patterns in the dynamics of carbon dioxide: one is market-led, one is market- and policy-led, and one is more development-oriented.

Keywords Carbon Kuznets curves · UN Rio convention · Policy events · Oil shocks · Intervention analysis · Structural breaks

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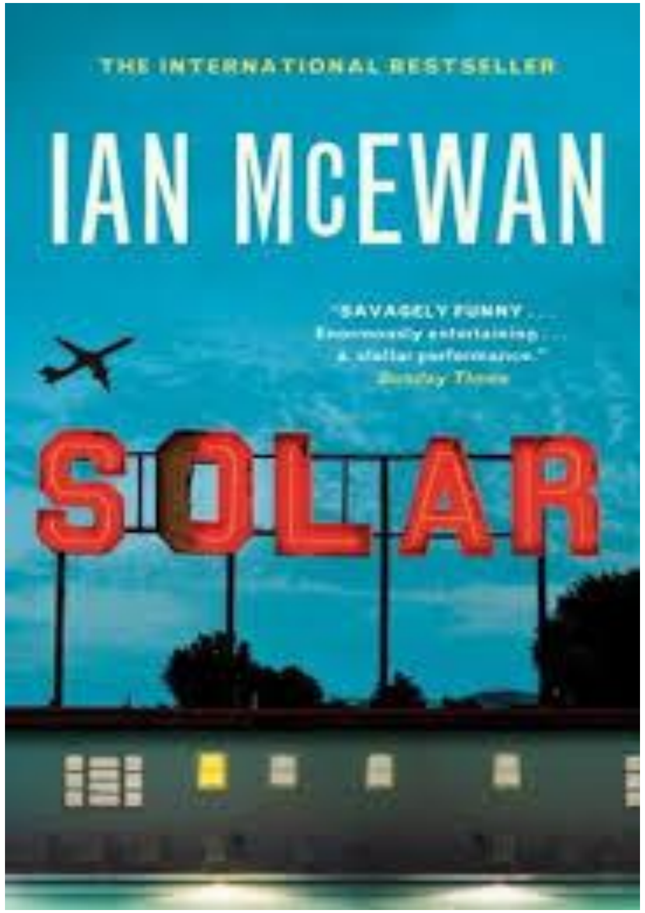
WEAK AND STRONG CROSS-SECTIONAL DEPENDENCE: A PANEL DATA ANALYSIS OF INTERNATIONAL TECHNOLOGY DIFFUSION

CEM ERTUR[a*] AND ANTONIO MUSOLESI[b,c]

[a] *LEO, Faculté de Droit d'Economie et de Gestion, University of Orleans, France*
[b] *Department of Economics and Management, University of Ferrara, Italy*
[c] *SEEDS, Ferrara, Italy*

SUMMARY

This paper provides an econometric examination of technological knowledge spillovers among countries by focusing on the issue of error cross-sectional dependence, particularly on the different ways—weak and strong—that this dependence may affect model specification and estimation. A preliminary analysis based on estimation of the exponent of cross-sectional dependence provides a clear result in favor of strong cross-sectional dependence. This result has relevant implications in terms of econometric modeling and suggests that a factor structure is preferable to a spatial error model. The common correlated effects approach is then used because it remains valid in a variety of situations that are likely to occur, such as the presence of both forms of dependence or the existence of nonstationary factors. According to the estimation results, richer countries benefit more from domestic R&D and geographic spillovers than poorer countries, while smaller countries benefit more from spillovers originating from trade. The results also suggest that when the problem of (possibly many) correlated unobserved factors is addressed the quantity of education no longer has a significant effect. Finally, a comparison of the results with those obtained from a spatial model provides interesting insights into the bias that may arise when we allow only for weak dependence, despite the presence of strong dependence in the data.


THE INTERNATIONAL BESTSELLER
IAN McEWAN
"SAVAGELY FUNNY . . .
SOLAR

Journal of Economic Geography (2014) pp. 1–33 doi:10.1093/jeg/lbu035

Econometric Modelling of the Regional Knowledge Production Function in Europe

*Sylvie Charlot**,**,†*, Riccardo Crescenzi**** *and Antonio Musolesi*****

*INRA, UMR 1215 GAEL, F-38000 Grenoble, France
**Université Grenoble Alpes, UMR 1215 GAEL, F-38000 Grenoble, France
***London School of Economics, Department of Geography & Environment, Houghton Street, London WC2A 2AE, UK
****Department of Economics and Management (DEM), University of Ferrara, Italy and SEEDS
†Corresponding author: Sylvie Charlot, UMR GAEL, Domaine Universitaire, 1241 rue des résidences, 38400 Saint Martin d'Hères, France.
email <sylvie.charlot@grenoble.inra.fr>

To model the complex relationship between patents and observable and unobservable determinants of new knowledge at the regional level, we propose a Generalized Additive Model (GAM) framework (Hastie and Tibshirani, 1990; Wood, 2004, 2008) and begin by estimating the following specification:

$$K_{r,t} = f_1(RD_{r,t}) + f_2(HK_{r,t}) + f_3(WRD_{r,t}) + f_4(WHK_{r,t}) + \alpha_r + \lambda_t + \gamma_r t + u_{r,t}, \quad (2.2)$$

where $f_1, \ldots, f_4$ are smooth functions and $\alpha_r + \lambda_t + \gamma_r t + u_{r,t}$ account for unobservable $U_{r,t}$. The existing empirical literature on the RKPF has focused on more constrained

Framework: the Knowledge production function

- The knowledge production function by Griliches (1990) is a kind of conceptual/causal framework for studying innovation activities at micro level.

In this paper

- **Focus on a Macro innovation setting**
- **New Technological paradigms and discontinuities**
- **Assess the effect of environmental policy (threshold effects, policy heterogeneity)**

Aims

- To enrich the methodological toolkit of policy → innovation analysis with more flexible and coherent instruments
- To emphasise a reflection upon model selection under ex ante model uncertainty (D Hendry legacy)
- To give food for thought to policy assessment analysis (by agencies)

RELATED RESEARCH

It complements recent papers that examine ‘directed technological change’ by observing clean technologies and policies **with a focus on micro and sector based evidence.**

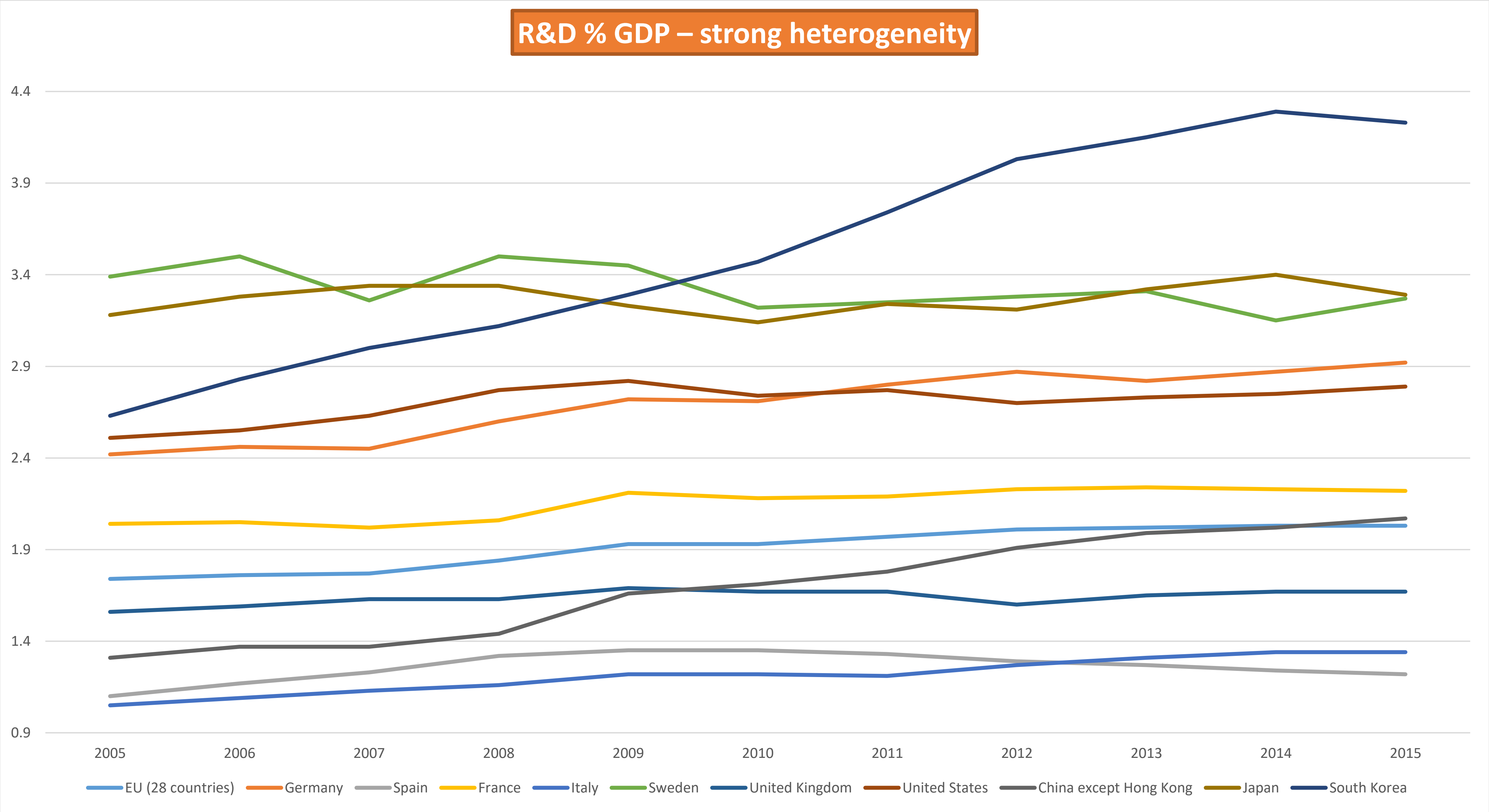
Among seminal papers, Acemoglu et al. (2016) analyse the transition to a decarbonised economy through technology and estimate the model by using firm level US energy sector data

Aghion et al. (2016) complement that analysis and provide evidence on the automotive industry sector, finding signs of path dependency in clean technological innovations, but also significant fuel tax effects.

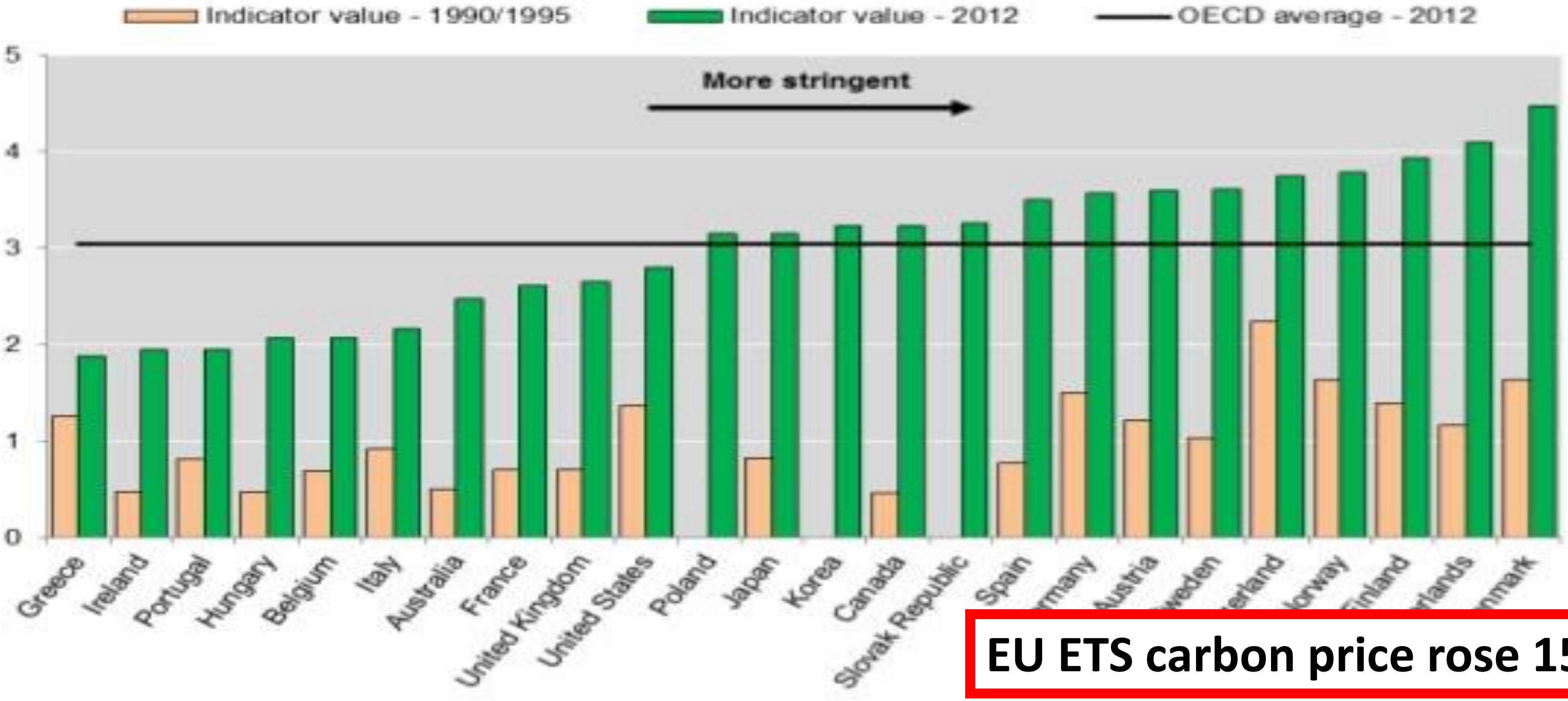
Related research (NEW macro)

- Nesta, L., Verdolini, E., Vona, F. (2018). Threshold Policy effects and directed technical change in energy innovation, FEEM nota di lavoro
- Fu, W., Li, C. Ondrich, J., Popp, D. (2018). `Technological spillover effects of state renewable energy policy: evidence from patent counts', NBER working paper 25390, December 2018

HINTS FOR A MACROECONOMICS ORIENTED RESEARCH AGENDA


R&D % GDP – strong heterogeneity
4.4
3.9
3.4
2.9
2.4
1.9
1.4
0.9
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
EU (28 countries)
Germany
Spain
France
Italy
Sweden
United Kingdom
United States
China except Hong Kong
Japan
South Korea

Environmental policy stringency has been increasing in OECD countries



EU ETS carbon price rose 150% over 2018

Botta, E. and Koźluk, T. (2014), *OECD Economics Department Working Papers*, forthcoming.

TWO RESEARCH ISSUES

1. In which way inventions inputs (R&D, human capital, spillovers and environmental policies) affect knowledge, with emphasis on ***nonlinearities, unobserved factors and model uncertainty.***
2. Whether and how environmental policy influences green knowledge, ***allowing for heterogeneous policy effects across countries (and over time).***

- Extending Popp (2019) research agenda on environmental policy and innovation

The data

Thanks to SEEDS team!

Green patents

- Data are collected from OECD-STATS database. We consider patents which comes under Selected Environment-related Technologies as defined by OECD (IPC: ENV_TECH) and granted at USPTO (United States Patent & Trademark Office)
- **We calculate the number of patents country-wise according to the inventor(s)'s country(ies) of residence.**
- We take into account family patents (and shared applications, which leads to fractional counts)
  - Alternative is to use per capita patents

Green patents and innovative inputs

- Stock of R&D calculated as in Coe et al (2009)
- Human Capital stock from PWT
- External R&D and Human capital >> weighted averages using geographic distance (exponential decay) as in Keller (2004) and Ertur and Musolesi (2017)
- **Panel data: 1982-2012, 19 OECD countries**

Policy indicators (discrete): extending the OECD EPS timeframe

- Discrete based policy indexes are derived from OECD sources and used as key policy indicators

- Nesta, Nicolli and Vona et al. (2014, JEEM)

- Varying over time and across countries
- **The policy index (AIR POLLUTION) we here exploit is binary**

To mitigate model complexity

ECONOMETRIC ISSUES AND MODELS

Nonlinearities and Unobserved common factors: additive semipara model

- We start by considering the following ***rather* general semiparametric specification**

$$GK_{it} = c_i + \alpha EP_{it} + g_1(RD_{it}) + g_2(HK_{it}) + g_3(WRD_{it}) + g_4(WHK_{it}) + \boldsymbol{\pi}_{\mathbf{i}}'\mathbf{F}_{\mathbf{t}} + \varepsilon_{it}$$

- We adopt the approach proposed by **Su and Jin (2012),** who consider a panel data model that extends the multifactor linear specification proposed by **Pesaran (2006)** and use **(penalized) spline functions (see Wood, 2017, Cardot and Musolesi, 2019)** for the nonparametric part of the model, **g(.)**
- **Multifactor error (**$\boldsymbol{\pi}_{\mathbf{i}}'\mathbf{F}_{\mathbf{t}}$): useful to address i) cross-sectional dependence and ii) endogeneity since the factors are allowed to be correlated with the explanatory Variables **(Ertur and Musolesi, 2017).** Useful for policy evalutaion **(Hsiao et al, 2015, 2016).**
- We adopt an additive structure instead of a fully nonparametric one to avoid the 'curse' of dimensionality…

Multifactor error structure

Common Correlated Effects

A semiparametric approach

Penalized Regression Splines

In PRS the following criterion is minimized:

$$\sum_{i=1}^{N}\{y_i - \phi(x_i)\}^2 + \lambda \int \phi''(x)^2 dx \quad \textbf{(univariate case)}$$

$\lambda \int \phi''(x)^2 dx$ is a measure of the *wiggliness* of ϕ.

The smoothing parameter λ controls the trade-off between smoothness of the estimated ϕ and fidelity to the data.

- $\lambda \to \infty \to$ straight line estimate for ϕ
- $\lambda = 0 \to$ unpenalized estimate

λ is selected by the restricted maximum likelihood (REML) estimation.

In this study:

- We use thin plate regression splines (TPRS) bases, which do not require knot selection and are computationally efficient.

Model uncertainty (and the myth of significance assuming known DGP)

- **Which is the true DataGeneratingProcess? (big issue)**
- In general, bias-efficiency tradeoff when comparing parsimonious to complex models
- Standard approach: assuming the DGP known and being represented by parametric models and then estimate the model (<u>At best, robustness checks</u>)
- We recognise **model uncertainty** by relying on **Nonparametric regression** and **model selection**
- We compare alternative specifications.
- For the observable variables, we consider both parametric linear models and semiparametric additive models

Results: Model selection

- It is found that **Linearity is rejected** and that the **individual trend specification** beats the others, following Wood et al. (2016), in JASA

Lowest BIC is preferred

Specification	*BIC*
1. Semiparametric additive smooth functions, individual time effects (random trend)	218.1777
2. Parametric, individual time effects (random trend)	235.3614
3. Parametric, multifactor error structure (CCE)	246.0169
4. Semiparametric additive smooth function, multifactor error structure (CCE)	282.6753
5. Semiparametric additive smooth function, two-way fixed effects	476.0993
6. Parametric, two-way fixed effects	604.5955

Preferred model for the Green knowledge Production Function

- *Nonlinear additive smooth functions* *Individual trends*

$$GK_{it} = c_i + \alpha EP_{it} + g_1(RD_{it}) + g_2(HK_{it}) + g_3(WRD_{it}) + g_4(WHK_{it}) + \pi_i t + \varepsilon_{it}$$

Highlights

- Individual time trends (random trend model, Heckman and Hotz, 1989; Wooldridge, 2005) is a compromise between time dummies and the multifactor model; the latter being very general but extremely inefficient (many nuisance parameters), the former parsimonious but impose common trend across countries.
- Individual effects + time dummies > Diff-Diff type estimators. Common trend assumption can be too restrictive in general and specifically for policy evaluation (see also Cardot and Musolesi, 2019ER)
- Additive nonparametric effects are in between the too restrictive parametric model (bad results available upon requests) and the very general fully nonparametric one (unfeasible with this data set).
- The choosen model is a compromise between a very general, but unfeasible (fully nonparametric) or very inefficient (additive and multifactor error) and too much restrictive models (various parametric specifications).

Key Econometric outcomes (two ‘policy models’)

1

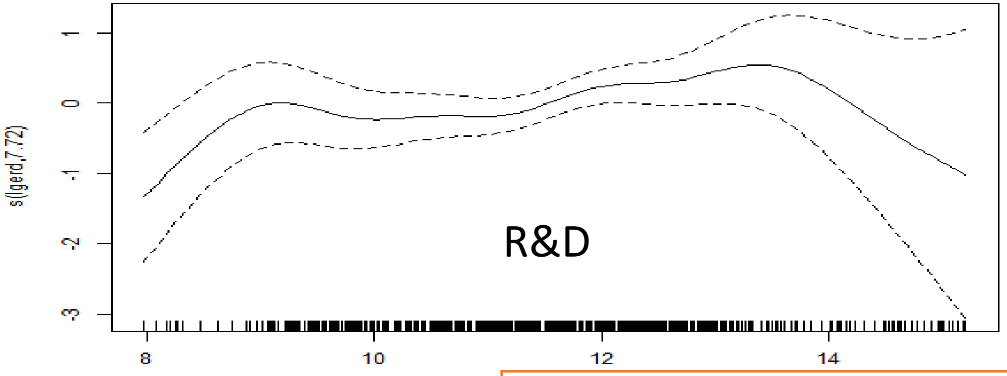
2

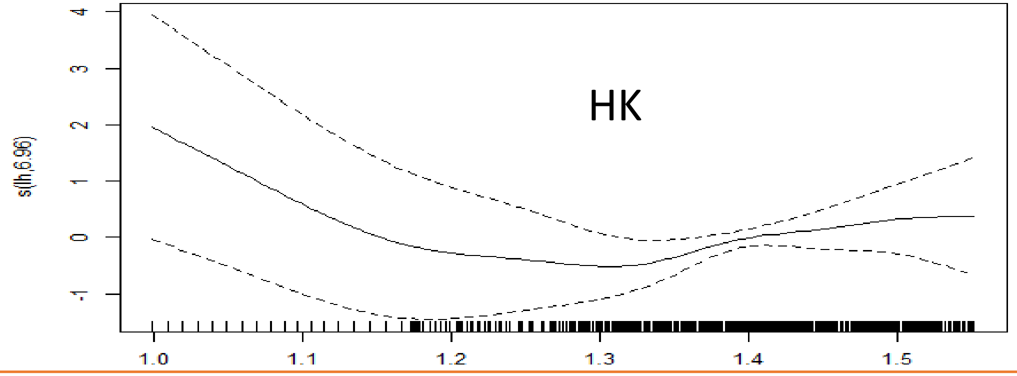
1

PARAMETRIC: policy_dummy **0.08893 (0.055361) – intercept shift**

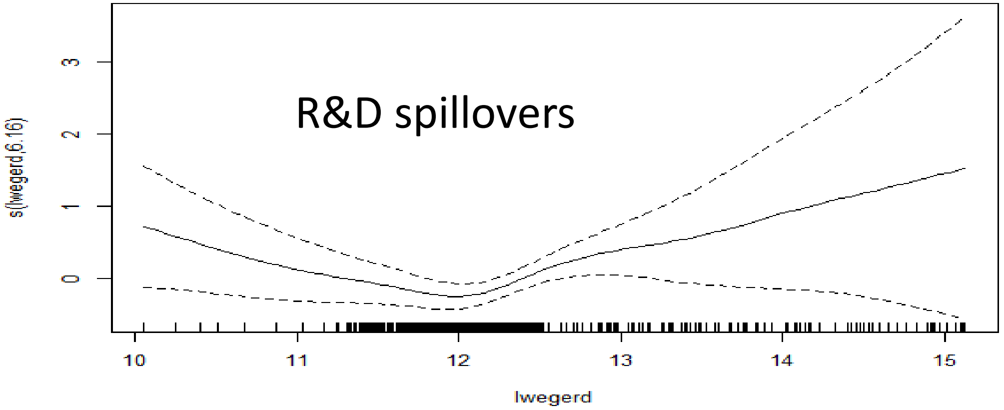
NON PARAMETRIC: R&D and Human capital

It is worth noting that the economic interpretation is easy, since the slopes do represent an elasticity (log)





Threshold effects, non linearities



HK spillovers not significant

Highlights

- **They all show rather complex nonlinear (but monotonic) relations, threshold effects that cannot be modelled by using parametric specifications**

Modelling Heterogeneous Policy effects

- We explore models in which the **effect of the policy may vary nonparametrically with the regressors**
- A variable selection procedure (Marra and Wood, 2011) lead us to retain only two significant variables that explain the heterogeneous effect of the policy: **R&D and WRD**
- Using an approximate ANOVA test procedure (Wood, 2017), an additive structure for the nonparametric function is strongly rejected in favor of a more general model based on **bivariate nonparametric regression function**:

$$\alpha_{it} = \alpha + f\,(RD_{it}, WRD_{it})$$

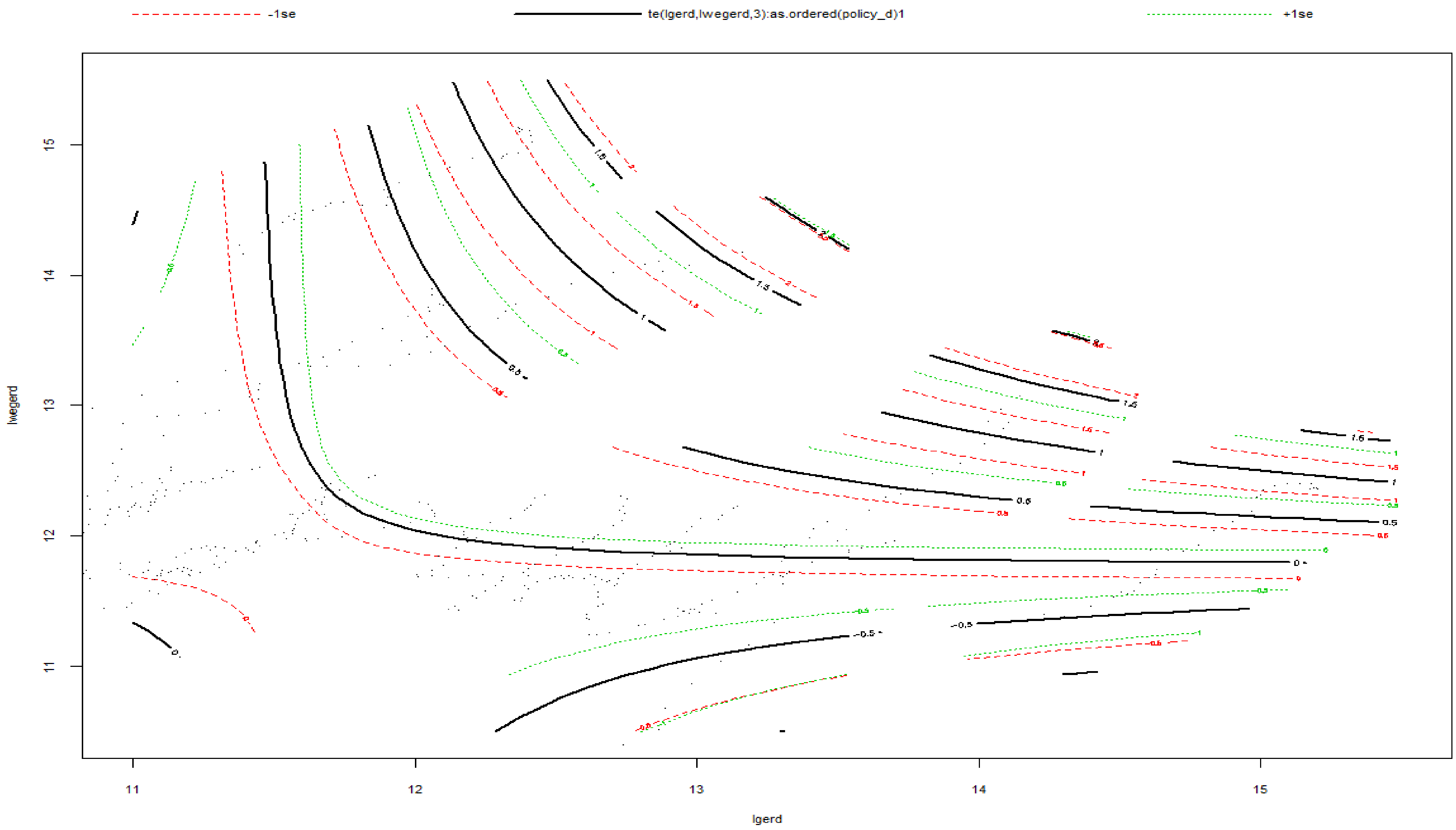
- $\boldsymbol{\alpha}$ **is the MEAN effect** of the policy and $\boldsymbol{f}\,(.)$ **indicates how the mean effect varies with RD and WRD → both intercept shift and f(x) change**

Heterogeneous Policy effects: results

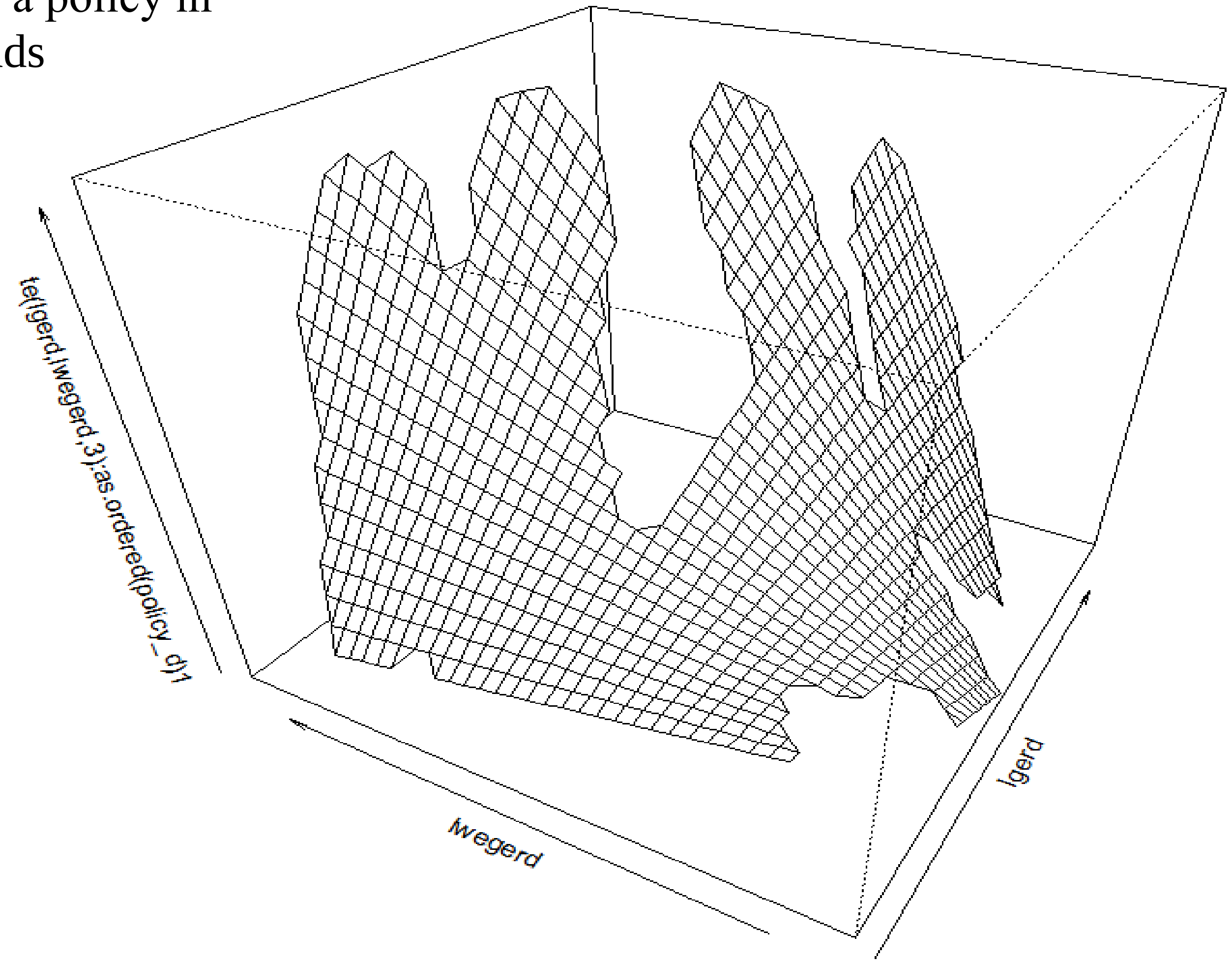
- The average effect of the policy is positive (0.15) ad highly significant (about 1%)

- the effect of the policy increases with both R&D and human capital with the estimated, f (RD_{it}, wRD_{it}), as figures below show.

The estimated effect of the policy (α_hat) is 0.15 + f(RD,WRD), which is depicted below



the larger knowledge investments are, the stronger the possible role of policy in inducing new inventions. The higher the combination of any R&D/human capital sources, including their spillovers, the stronger socio-technical system capacity to absorb the effect of the policy, translating this into inventions. The economic system absorptive capacity is the ability to recognize the value of new external ‘information’, a policy in this case, assimilate it, and apply it to invention ends



Final remarks

(1) threshold effects and nonlinearities are relevant features of the data which are obscured in parametric specifications

Relevant policy implications: i) critical mass of both RD and HK is necessary……

(2) The Heterogenous policy effect is a function that increases with R&D and WR&D (R&D is controlled by the country)

Working towards results………….

Multifactor error structure

Assume:

$$e_{it} = \gamma_i' \mathbf{f}_t + \varepsilon_{it}$$

where:

- $\mathbf{f}_t$: unobserved common factors
- ε_{it}: idiosyncratic errors, assumed independent of $(\mathbf{d}_t, \mathbf{x}_{it})$

$\mathbf{f}_t$ is modeled to be correlated with $(\mathbf{d}_t, \mathbf{x}_{it})$ through:

$$\mathbf{x}_{it} = \mathbf{A}_i'\mathbf{d}_t + \mathbf{\Gamma}_i'\mathbf{f}_t + \mathbf{v}_{it}$$

where:

- $\mathbf{A}_i$, $\mathbf{\Gamma}_i$: factor loading matrices
- $\mathbf{v}_{it}$: distributed independently of the common effects and across i

Common Correlated Effects

CCE (Pesaran, 2006; Su and Jin, 2012) introduces a finite number of unobserved common factors and proxies $\mathbf{f}_t$ using cross-sectional averages:

$$\bar{\mathbf{z}}_t = N^{-1} \sum_{j=1}^{N} \mathbf{z}_{jt}$$

CCE properties

- easy to implement: run an auxiliary regression augmented with cross sectional averages (y and x)
- standard with macro panel: SURE but unfeasible with increasing N
- CCEP and CCEMG (Pesaran and Smith, 1995, for MG estimator)
- valid even if the DGP has common factors and spatial error dependence (Pesaran and Tosetti, 2011)
- still valid if the true DGP has finite strong factors but also infinite number of weak factors (Chudik et al., 2011)
- still valid when the unobserved factors are allowed to follow unit root processes (Kapetanios et al., 2011)

A semiparametric approach

$$y_{it} = \alpha_i^{'} \mathbf{d}_t + g\left(\mathbf{x}_{it}\right) + e_{it}, \tag{3}$$

where:

- g: the function of interest
- $\mathbf{d}_t$: observed common effects

For $\mathbf{d}_t = \mathbf{1} \rightarrow$ "one way" fixed effect specification

Assumption (*for identification*): $E(g\left(\mathbf{x}_{it}\right)) = 0$

Su and Jin (2012) consider the problem of estimating panel data models by extending the CCE approach to nonparametric specifications.

$$\Downarrow$$

In this work we employ Su and Jin's (2012) approach, which extends the CCE and use regression spline to estimate the nonparametric component.

Regression Splines

Main idea: Approximate each function with a basis expansion. E.g., for ϕ:

$$\phi(x) = \sum_{j=1}^{k} b_j(x)\beta_j$$

where:

- k: the dimension of the basis
- $b_j, j = 1, \ldots, k$: a predefined spline basis
- $\beta_j, j = 1, \ldots, k$: parameters

Characteristics

- low rank smoothers $\rightarrow$ computationally attractive
- choice of k $\rightarrow$ a degree of subjectivity into the model fitting process
- do not penalize roughness

Penalized Regression Splines

In PRS the following criterion is minimized:

$$\sum_{i=1}^{N}\{y_i - \phi(x_i)\}^2 + \lambda \int \phi''(x)^2 dx \quad \textbf{(univariate case)}$$

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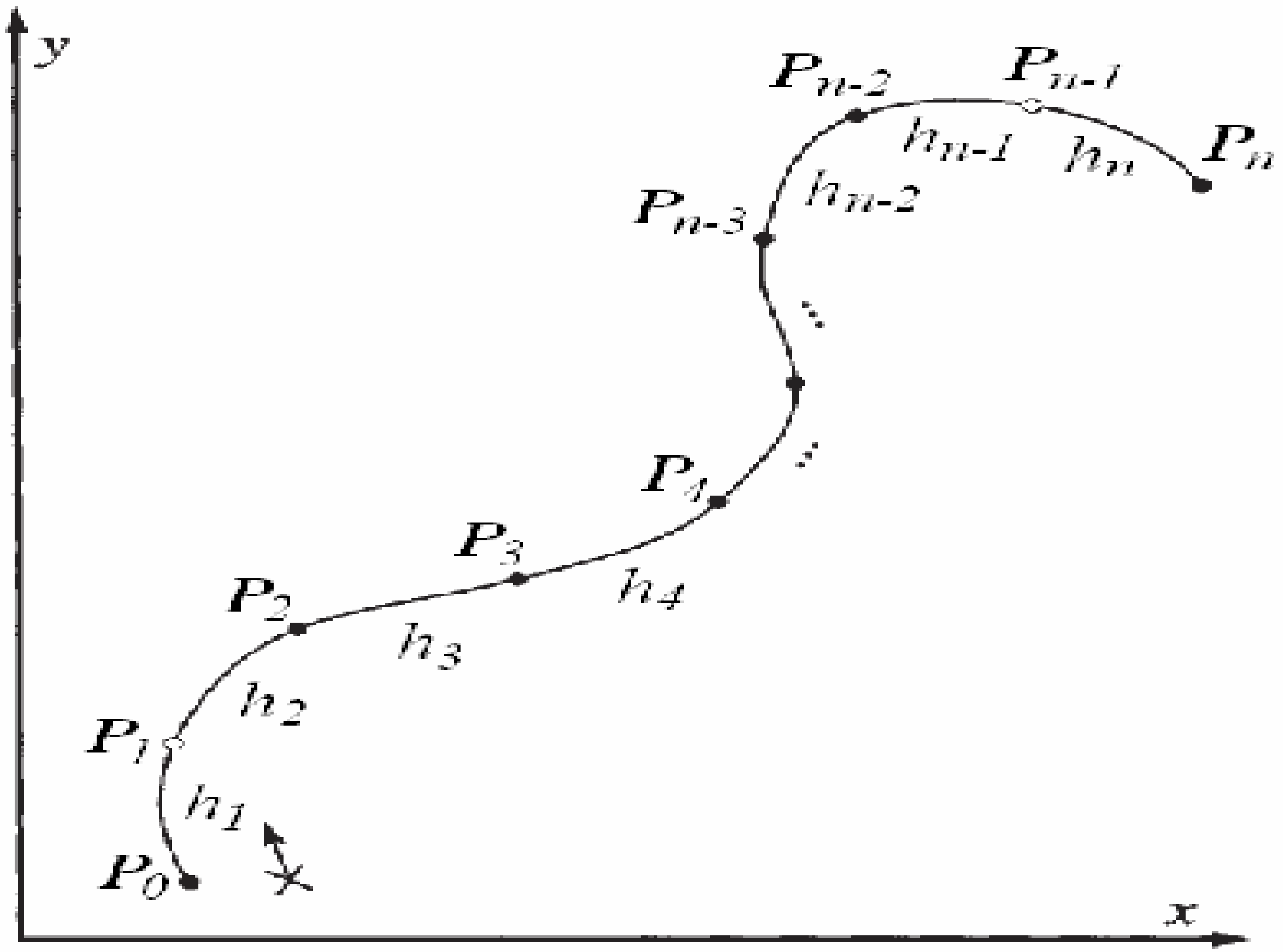
y
x
P_0
P_1
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