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Thesis title:

ESSAYS IN ENERGY AND ENVIRONMENTAL ECONOMETRICS: ELECTRICITY DEMAND, POWER PRICES AND THE EFFECTS OF CLIMATE CHANGE ON HEALTH

PhD in	ECONOMICS
Cycle	XXI
Candidate's tutor	MASSIMILIANO MARCELLINO
Year of discussion	2010

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Essays in Energy and Environmental Econometrics: Electricity Demand, Power Prices and the Effects of Climate Change on Health

Thesis in partial fulfillment of the requirements for the academic degree of
Doctor of Philosophy in Economics (XXI cycle).

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Contents

Introduction

Energy is an essential input for any economic activity. At the same time, energy production has a large impact on the environment.

For both reasons the structure and functioning of the energy sector have historically been a core subject of economic research and are acquiring an even greater importance.

Econometric tools provide stronger basis to understand the structure of energy markets, and add quantitative arguments that facilitate the choice of best strategies for its improvement. Moreover, econometrics leads to robust forecasts of energy matters and their environmental impacts.

Within energy the electricity sector is acquiring a growing importance (the fact that almost all developed countries have decreasing energy intensities but increasing electricity intensities can be taken as a row indicator of its raising role).

Market liberalization brought to radical and encouraging changes primarily in the power industry.

Moreover, policy measures aiming at protecting the environment have led to a stringent regulation of the electricity sector.

The previous arguments have made electricity a sector evolving rapidly in terms of the structure of supply and demand, and consequently power prices and risk management.

These features of electricity markets make it necessary to use flexible modeling strategies to investigate their functioning and dynamics.

In this thesis econometric approaches that allow for coefficients varying over time and the adjustment mechanism being non linear are adopted. In particular, in Chapter I a Bayesian approach and time varying parameters vector autoregressive models are used for forecasting monthly electricity demand in Italy. The second chapter aims at investigating the degree of efficiency in forward European electricity markets using threshold cointegration and min-max techniques. The last chapter deals with the effects of climate change on health. It reviews recent contributions grounded on quantitative analyses and provides a taxonomy of the adopted methodologies.

I thank my colleagues at Bocconi University and at Enel S.p.A., and the coauthors of the last chapter, Matteo Manera, Aline Chiabai, Anil Markandya for useful suggestions and comments. I am specially indebted to my advisor, Massimiliano Marcellino, and co-advisor, Luca Sala. I am grateful to my friends and family for their patience. To my husband, who in the last months put up with me without putting me down, I dedicate my thesis.

Part I

Time Varying Parameters Bayesian Forecasting of Electricity Demand: the Italian Case

Abstract

Electricity demand is modeled as a time-varying parameters (TVP) vector autoegression with or without imposing cointegration. The paper applies Bayesian strategies where all or a part of the parameters are allowed to vary, and compares their forecasts performances with alternative time series models, namely a seasonal ARIMA (SARIMA) specification and a vector error correction model (VECM). Considering Italian data, the appropriate diagnostic tests and estimation results are in favour of non-stability of the parameters. However, the forecasts abilities of the models do not show significant differencies when measured by RMSE and MAE, and compared trough the Diebold Mariano statistic. On the other hand, forecast intervals of Bayesian models show higher empirical coverage rates.

1 Introduction

Considerable attention has been devoted to the analysis and forecast of electricity consumption by researchers and praticitioners in the past several decades.

In early works, the estimation of electricity demand had been done by simultaneous structural equation models (e.g.Fisher and Kayser, 1962). Subsequently VAR and, since the papers by Engle and Granger (1987) and Engle et al. (1989), ECM models had become the standard techniques for electricity demand analyses. Further developments have relied on the use of Johansen (1988, 1995) method for estimating the long run relationship, while some attempts have adopted alternative approaches that increase the flexibility of the modelling strategies. For instance, Joutz et al. (1995) have used a Bayesian specification that allows to account for researcher's priors, while Chang and Martinez-Chombo have introduced a time varying parameters (TVP) specification to capture the evolution of the parameters over time.

Despite the big amount of studies on electricity, a much smaller number of attemps provide an explicit comparison of the forecasting performances of differnt models and none of them, at least among published works and to my knowledge, refers to the Italian market. There is therefore the need to quantify how, and to what extent, forecasts are sensible to the choice of the modeling strategy.

In the present study BVAR approaches with time varying parameters (TVP) and that may include cointegrating relations are compared with alternative time series models, namely an univariate Seasonal ARIMA (SARIMA) specification and a Vector Error Correction Model (VECM). The first model gives flexibility and exploits all available information explicitly; the second approach is appealing for its simplicitly, and third specification has become standard practice among researchers, and therefore both the last two provide natural benchmarks for comparison. By anticipating the results of this study, despite their differences, the three models do not lead to remarkable differences for forecasting aims.

These results are obtained using monthly Italian data for the period that spans from January 1990 to February 2009. A basic electricity demand equation is used, where consumption is regressed on industrial production, two series that account for calendar effects, proxies of the temperature, and eleven seasonal dummies.

Althought a demand equation is considered, prices are not included among the regressors. The main reason relies on the monthly frequency of the data and the forecasts. In the short run the demand of electricity and the possibility of switching to alternative energy sources (e.g. natural gas and distillate fuel oil) are constrained by a fixed stock of using appliances (see Silk and Jouts, 1997). Indeed, results from applied research show, on average, moderate responsiveness of electricity consumption to changes in prices (see among others: Engle et al., 1989; Filippini, 1999; and Fan and Hyndman, 2008, for a recent literature review.) Finally, an indication 'ex-post' of the validity of omitting the prices is obtained by regressing the estimated residuals from the SARIMA and VECM models on the logs of PUN baseload electricity prices[1]. The resulting coefficient does not appear significant.

The remaining part of the paper is organized as follows: the next section analyses the main features of the series and their integration properties; the models and estimations' results are presented in section 3; section 4 discusses the forcasting performance of the models, and section 5 concludes.

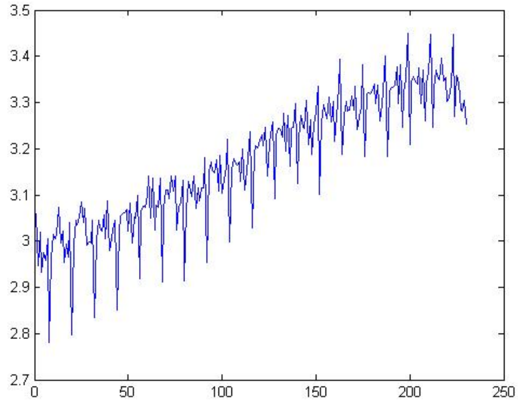
2 Data analysis and transformation

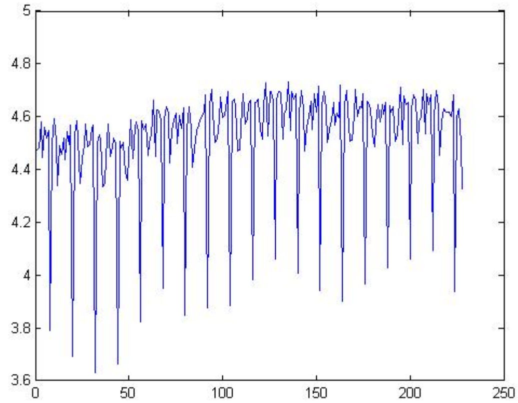
Electricity demand function is estimated using the logarithms of the electricity consumption (el). As explanatory variables, the log-transformed industrial production index (ip), cooling (CD) and heating (HD) degree days, two series that control for the calendar effect (CA) and the leap year effect (LY) are included in the models.[2] The plots of the variables are reported below, while more precise definitions of the series are given in the Appendix. Lower cases stand for log-transformation of the series.

As a first step of the analysis the presence of unit roots at seasonal as well as the zero frequency is detected. Among the procedures that have been developped, the one of OCSB (Osborn et al. 1988) and HEGY (Hylleberg et al. 1990) are employed here. The former allows to test the adequacy of the double filter $(1-L)(1-L^s)$; the latter tests whether $(1-L^s)$ may be preferred

[1] Monthly averages from 2005.1 to 2009.2 are used; an MA(3) term is added to correct for residual correlation

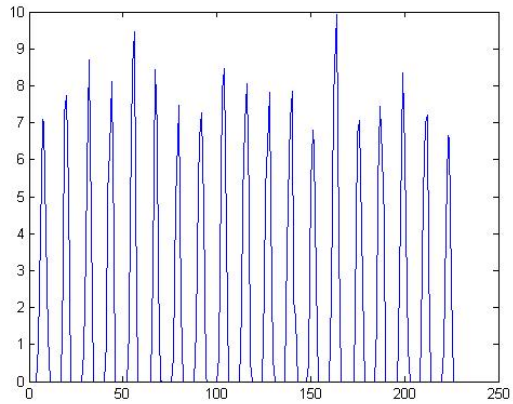
[2] The reason for using IP (instead of alternative indicators, e.g. GDP) as income variable is primary practical: while monthly records are provided for Italian industrial production, only quarterly data are available for GDP. Second, electricity consumption is widely known to be a good predictor of GDP (in other words the causal link is from electricity to GDP), while the causal relationship between electricity and IP is in both directions.

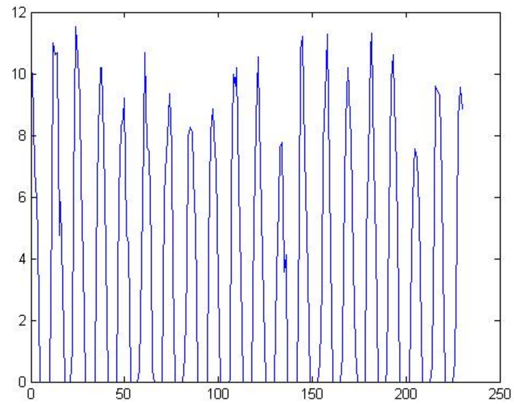




(a) Logs of electricity demand (TWh), 1990.2 - 2009.2

(b) Logs of industrial production (2000=100), 1990.2 - 2008.12





(c) Cooling degree days, 1990.2 - 2009.2

(d) Heating degree days, 1990.2 - 2009.2

Figure 1: Plot of series

to one of its components. Moreover, to investigate whether these filters lead to improved forecasts, the predictive performance of univariate models based on alternative transformations of the series is considered.

The OCSB method considers the auxiliary regression:

$$\phi_p\left(L\right)\Delta_1\Delta_{12}y_t=\sum_{s=1}^{12}\delta_s d_{s,t}+\pi_1\Delta_{12}y_{t-1}+\pi_2\Delta_1 y_{t-12}+\epsilon_t \tag{1}$$

where the order p of the polinomial $\phi_p(L)$ is chosen such that the estimated residuals are approximately white noise. It holds that if $\pi_2 = 0$ the filter Δ_{12} is appropriate, and if $\pi_1 = \pi_2 = 0$ the double filter $\Delta_1\Delta_{12}$ is needed. Table 1 shows the estimates of (1).

Variable	lags	$t(\pi_2)$	$F(\pi_1, \pi_2)$
el	$1, 12$	-6.895^{**}	23.779^{**}
ip	$1, 2, 5, 10$	-3.232	6.903

Table 1: **OCSB method**; $**$ denotes significance at the .05 level; 'lags' refers to the lagged $\Delta_1\Delta_{12}$ variables included in the auxiliary regression

The second approach involves the HEGY regression, which in case of monthly data is (see Franses, 1991):

$$\begin{aligned}\phi(L)\,\Delta_{12}y_t &= \mu + \sum_{i=1}^{11}\gamma_i D_{it} + t_t + \psi_1 y1_{t-1} + \psi_2 y2_{t-1} + \psi_3 y3_{t-1} + \\ &+ \psi_4 y3_{t-2} + \psi_5 y4_{t-1} + \psi_6 y4_{t-2} + \psi_7 y5_{t-1} + \psi_8 y5_{t-2} + \\ &+ \psi_9 y6_{t-1} + \psi_{10} y6_{t-2} + +\psi_{11} y7_{t-1} + \psi_{12} y7_{t-2}\end{aligned} \tag{2}$$

where the auxiliary regressors are appropriately defined as in Franses (1998).
The component hypothesys $\psi_1 = 0$, $\psi_2 = 0$, $\psi_3 = \psi_4 = 0$, $\psi_5 = \psi_6 = 0$, $\psi_7 = \psi_8 = 0$, $\psi_9 = \psi_{10} = 0$, $\psi_{11} = \psi_{12} = 0$ correspond to separate tests for the unit roots contained in the real valued $(1 - L)$, $(1 + L)$, $\left(1 + L^2\right)$, $\left(1 + L + L^2\right)$,$\left(1 - L + L^2\right)$, $\left(1 + 3^{1/2}L + L^2\right)$, $\left(1 - 3^{1/2}L + L^2\right)$ respectively.
The results of the test performed on the series el and ip are reported in Tables 2 and 3.

The results of the OCSB and HEGY tests, reported in Tables 1 - 3, suggest conflicting interpretations of the type of seasonality in the series. To solve this apparent conflict Table 4 and Table 5 report the one-step ahead and multi-step ahead forecasts of the series. To evaluate the set of forecasts the observations from 1990m1 to 2003m12 are used for the estimation and forecasts are generated for the sample 2004m1-1204m12. The reason for choosing this sample is that the years next to 2004 registered temperatures abnormally high or low. The RMSE is the evaluation criterion. Only models that passed the tests on residuals autocorrelation are reported.

Test	t-stat	F-stat
t_1	-1.472	
t_2	-2.427*	
w_1		1.240
w_2		5.259*
w_3		2.448
w_4		4.982*
w_5		1.634

Table 2: **HEGY method**; variable el; no trend; $*$ and $**$ denote significance at the .10 and .05 level, respectively; critical values are reported in Franses(1991)

Test	t-stat	F-stat
t_1	-2.963*	
t_2	-2.434*	
w_1		10.270**
w_2		6.911**
w_3		1.551
w_4		11.224**
w_5		1.523

Table 3: **HEGY method**; variable ip; trend; $*$ and $**$ denote significance at the .10 and .05 level, respectively; critical values are reported in Franses(1991)

For the series el, the one-step ahead RMSE is smaller for the $ARMA(1, 12; 1)$ model on the untrasformed series; while for the multi-step ahead the same model on the differences of el has the smallest RMSE. In contrast with the results for el, considering the series ip the model for the variable transformed according to the HEGY test outperforms the other models on both, one-step and multi-step ahead.

In sum, it may be concluded that a small number of imposed unit roots leads to better forecasts for the variable el. Therefore, the $(1 - L)$ filter is used for this variable in the remaining of the paper. As for the variable ip the forecast evaluation and the HEGY test (in contrast with the OCSB method) provide evidence of some seasonal unit roots. In particular, according to the results of the HEGY test, ip should be substituted by $ip^* = \left(1 - 3^{1/2}L + L^2\right)\left(1 - L + L^2\right) ip$ before analysing the cointegration between el and ip^*. However, this filter does not seem to lead to good results in our particular case, and it appears more opportune to treat this variable as integrated of order one at the zero frequency only.

Filter	Levels	Δ_1	Δ_{12}	$\Delta_1\Delta_{12}$
Model	$arma\,(1, 12; 1)$	$arma\,(1, 12; 1)$	$arma\,(2, 1)$	$ma\,(1, 12, 13)$
Determ.	t,d	d	-	-
$1 - step$	.361	.390	.625	.392
$h - step$	.375	.353	.726	.370

Table 4: Univariate models for **electricity demand RMSE for 2004.1 - 2004.12**; for each filter the reported specification is the one that minimizes the BIC among those with not significant LM of order 2; all RMSE refer to the original electricity demand series

Variable	Levels	Δ_1	Δ_1	$\Delta_1\Delta_{12}$
Model	$ar\,(1, 12)$	$arma\,(1, 12; 1)$	$ma\,(1, 12, 13)$	$ma\,(1 - 5)$
Determ.	t,d	d	-	-
$1 - step$	3.342	3.205	4.223	2.526
$h - step$	3.601	2.377	3.817	2.051

Table 5: Univariate models for **industrial production RMSE for 2004.1 - 2004.12**; for each filter the reported specification is the one that minimizes the BIC among those with not significant LM of order 2; all RMSE refer to the original industrial production series

3 Modeling strategies

3.1 Preliminary methods

3.1.1 Univariate analysis

In the previous section it has been shown that the ARIMA($p = 1, 12; q = 1$) specification outperforms for modeling electricity consumption all other univariate model. Estimation results are reported in Table 6.

3.1.2 Fixed coefficient VECM

Having assesed that series present unit roots, in this section the existence of cointegration is checked for. In particular, the series of the electricity demand and the industrial production, which appear to be integrated at the zero frequency, may show non-seasonal cointegration. Adopting the method proposed in Johansen (1988), the starting point of the cointegration analysis is a VAR specification for the $nx1$ vector of $I(1)$ variables X_t:

$$X_t = A_1 X_{t-1} + \ldots + A_p X_{t-p} + \Psi D_t + u_t \tag{3}$$

where D_t contains deterministic components, and u_t, is an $nx1$ i.i.d. Gaussian error vector. Equation (3) can be reparametrized as:

$$\Delta X_t = \Pi X_{t-1} + \Pi_1 \Delta X_{t-1} + \ldots + \Pi_{p-1} \Delta X_{t-p+1} + \Psi D_t + u_t \tag{4}$$

where $\Pi = -(I_n - A_1 - \ldots - A_p)$, $\Pi_i = -(I_n - A_1 - \ldots - A_i)$, $i = 1, \ldots, p-1$, which is the VECM representation of the original VAR system (see, among others, Charemza and Deadman, 1992). If cointegration among the variables X_t is present, model (4) includes both long-run and short-run stationary components. The maximum likelihood method by Johansen tests the presence of cointegration at the systems level by determining the rank of the long-run matrix, Π. If $rank\Pi = r$, with $0 < r < n$, the matrix Π can be decomposed as $\Pi = \alpha\beta'$, where α, is an nxr matrix of adjustment parameters and $\beta$is an nxr matrix containing the r cointegrating relations among the variables in X_{t-1}. The Johansen approach enables to estimate the parameters β, and to assess the number of $I(0)$ linear combinations among the X_t variables.

$Variable$	$Coefficient$	$StdError$
C	-0.044**	0.006
$\Delta el(-1)$	-0.446**	0.057
$\Delta el(-12)$	0.108**	0.042
$D1$	0.023**	0.005
$D2$	-0.053**	0.007
$D3$	0.024**	0.007
$D4$	-0.030**	0.010
$D5$	0.026**	0.013
$D6$	0.011	0.015
$D7$	0.004	0.017
$D8$	-0.218**	0.021
$D9$	0.022**	0.017
$D10$	0.119**	0.015
$D11$	0.017**	0.007
RU	0.002**	0.000
LY	0.043**	0.008
HD	0.006**	0.001
CD	0.013**	0.002
$MA(1)$	0.488**	0.085
$R2 = 0.973$	$LM(4) = 1.747$	$LM(5) = 1.4$

Table 6: **SARIMA model** - Estimation results; $*$ and $**$ denote significance at the .10 and .05 level, respectively

In the present case, X_t consists in the logged electricity demand and industrial production, while D_t includes a constant, the series that account for calendar and temperature effects and seasonal dummies. As suggested in Johansen (1995), the dummies are orthogonalized on the constant $1/12$, in such a way that they do not generate a trending term. Since one cointegrating relationship is found among the variables, this is included in the model that can be written in

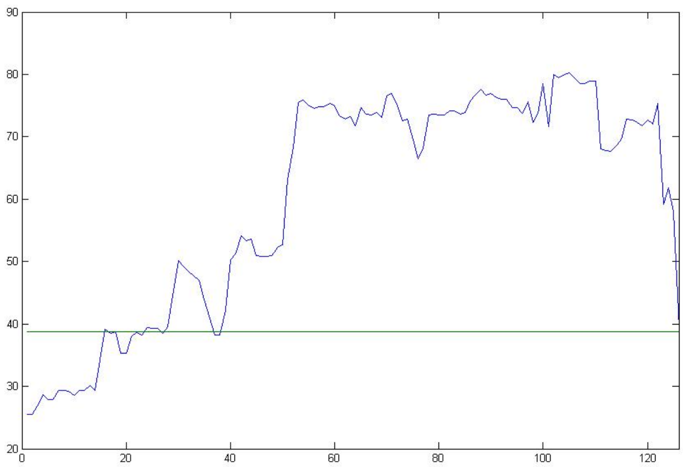


Figure 2: Chow test sequence and relevant Andrews critical value

the VECM form[3]. The estimation results related to electricity demand equation for the whole sample (1990.1 - 2008.12) are reported in the Table 7. Based on diagnostic checks, the estimated specification appears satisfactory.

3.1.3 Stability analysis

Over the last seventeen years the response of electricity consumption to its determinants may have changed in several ways (see Bertoldi and Atanasiu, 2007). For example, it is possible that an increase in summer temperatures (captured by the series of CD) has a larger impact now than in 1990, and this could be due to the diffusion of cooling appliances or, possibily, a changement in people's utility function. Alternatively, the adgiustement to the long-run equilibrium may have varied over time, or it could be the case for other factors. There are different types of tests for parameters stability (see for example Marcellino, 2002). Here, the methods of Quandt (1960) and Nyblom (1989) are adopted. The first tests the hypothesis of parameters stability (of the demand equation) against the alternative of a single break at unknown date. In particular, the method of Quandt (1960) considers the maximum value of the Chow test computed recur-

[3]The same variables appear in both equations. HD and CD shouldn't be very helpful to predict industrial production. However, the estimated coefficients are so small, that they may imply little distorsion.

Variable	Coefficient	StdError	li
$ect(-1)$	-0.218**	0.062	0.149
$\Delta el(-1)$	0.222**	0.073	0.124
$\Delta ip(-1)$	-0.194**	0.031	0.052
$\Delta el(-2)$	0.223**	0.066	0.036
$\Delta ip(-2)$	-0.141**	0.029	0.018
$MA12el(-1)$	-0.395**	0.063	0.059
$MA12ip(-1)$	0.081**	0.030	0.191
$d1$	0.016**	0.007	0.046
$d2$	-0.071**	0.008	0.19
$d3$	0.081**	0.009	0.041
$d4$	-0.041**	0.011	0.091
$d5$	0.053**	0.012	0.1
$d6$	-0.010	0.016	0.205
$d7$	-0.004	0.018	1.051
$d8$	-0.273**	0.019	0.990
$d9$	0.049**	0.022	0.14
$d10$	0.093**	0.022	0.433
$d11$	0.067**	0.019	0.722
ru	0.002**	0.000	0.223
ly	0.035**	0.008	0.176
hd	0.004**	0.001	0.783
cd	0.013**	0.002	1.336
c	-0.031**	0.006	0.255
	$R2 = 0.973$	$LM(5) = 3.178$	$LC = 8.235$

Table 7: **VECM** Estimation results for electricity demand equation; li and LC stand for, respectivey, the single coefficient and the cumulative results of Nyblom statistic; $*$ and $**$ denote significance at the .10 and .05 level, respectively

sively for every possible breakdate[4]. The tests' sequence is reported in Figure (3.1.3) together with the opportune critical value (Andrews, 1993). As it appears from the graph, the sequence of Chow test lies above Andrew's critical value at several dates, suggesting instability of the parameters. Indeed, as it is possible that this conclusion is distorted by the presence of seasonal dummies in the equation, the test is repeated over series previously adjustded for seasonality. The results still reject the null, and thus confirm the ropture with the hypothesis of parameters' constancy. Second, to better assess the nature of the instability a further method (Nyblom 1989, Hansen 1992) that allows for breaks at unknown dates as well as random walks parameters is adopted.

Since the interest is in the dynamics of the VECM, the test is applied to the coefficients of I(0) variables. In practice since the model is unrestricted and it includes exogenous variables, it is estimated through a two-step procedure (1st step: cointegrating eq. Johansen; 2nd step OLS). The second stages are re-estimated and Nyblom tests are performed. The results for the electricity equation are shown in Table 7. According to the above figures, the joint statistic rejects the null of stability at the 1 percent level. Single-coefficients tests show instability due to the impact of Summer months (june-october), HDD and CDD. The remaining variables appear more robust over the sample.

3.2 TVP - BVARs with or without cointegration

As above seen, the results of the stability tests suggest that coefficients may vary over time. Here, (4) is replaced by:

$$\Delta Y_t = B_t X_t + E_t \tag{5}$$

$$B_t = [A_{1t}, \Omega_t] \tag{6}$$

$$X_t = \left(\Delta Y_{t-1}', Z_t\right)' \tag{7}$$

where the evolution path of the parameters is defined as:

[4]As suggested in Hansen (2001) the top and bottom .15 of dates' series is discarded

$$
\begin{aligned}
\tilde{\beta}_t &= F\tilde{\beta}_{t-1} + \eta_t && (8)\\
\tilde{\beta}_t &= \beta_t - \bar{\beta}_0 && (9)\\
\beta_t &= vec\left(B_t^{'}\right) && (10)
\end{aligned}
$$

The regressors' vector X_t has size $(kX1)$, where k is given by the number of equations times lags plus the rows' number of Z_t. The adopted approach is to treat (5) as a simple VAR model for ΔY_t, possibly augmented with the inclusion of the disequilibrium term (previously estimated using classical techniques) as an additional regressor in a Bayesian VAR framework (see Alvarez and Ballabriga, 1995; and Amisano and Serati, 1999). The vector Z_t includes the seasonal dummies, the correctors for calendar effects, the series HD and CD and may include the cointegrating vector.

Equations (5) and (8) consitute the measurement and state equations of a state-space representation, wich is the standard framework for estimating TVP models.

The error terms of the m observed y_t and the K unobserved β_t components are assumed i.i.d. normal distributed, with $E\left(\eta_t \epsilon_t^{'}\right) = 0$[5]. The parameters evolve as a random walk. The prior for the initial state of the time-varying coefficients is Normal. The inverse variance-covariance matrices of both, the measurement and the state, equations are assumed to follow the Wishart distribution (conjugate priors). The matrix F in (8) is set to be the identity matrix, that is the parameters follow a random walk[6].

The sample is split in two parts. The first set of observations are used to calibrate the parameters of the prior distributions. In particular, the mean and the variance of B_0 are chosen to be the OLS point estimates on the initial subsample and their variances. The degrees of freedom, ν_n and ν_β, of the Wishart distributions are set to be, respectively, 6 and 100 plus the dimension of each matrix[7]. The parameter ν_β is chosen in such a way to shrink the distribution of

[5]Here the var-cov matrix is assumed to be block-diagonal. Refer among others to Cogley and Sargent (2001) and Amisano and Federico (2004) for examples of non block diagonal forms.

[6]Note that in model (5) - (8) the only source of variability are model's coefficients, while the variance and covariance matrix of the shocks is assumed constant over time (see Primiceri, 2005; and Cogley et al. 2008 for a different approach on this point).

[7]The degrees of freedom exceed the dimension of the Wishart for both, the measurement and the state, equations and therefore the inverse Wishart are proper.

μ_0	μ_{OLS}
Σ_0	Σ_{OLS}
ν_n	m+6
ν_β	K+100
k_n	10
k_β	10^6

Table 8: Hyperparameters

the parameters. The scale matrices are chosen to be diagonal matrices, labeled $S_n = k_n I_t$ and $S_\beta = k_\beta I_z$ for the precision matrices of the measurement and state equations. Table 8 summarize the hyperparameter of the model.

The posterior distributions of the parameters are obtained by performing the Kalman filter (forward recursion) and the smoothing techniques of Carter and Kohn (1994) (backward recursion that allows to reconstruct the in sample evolution path of the β_s by using the complete set of the information). The final estimates of the states for the electricity demand equation are reported in table 9 and table10. Selected time-varying coefficients are reported in Figures 3 and 4.

3.2.1 BVAR models with coefficients partly varying and partly constant

The need to estimate a large number of parameters can worsen the performance (particularly out-of-sample) of TVP-BVAR models in some empirical applications. In order to reduce the dimension of paremeters space, equation (5) can be replaced by:

$$\Delta Y_t = B_t X_t + \Gamma W_t + \epsilon_t \tag{11}$$

where impacts of the variables in W_t are assuned constant over time.[8] In practice, only the coefficients with hightest evidence of instability are ellowed to vary: i.e. X_t includes the lagged dependent variables, $D7$, $D8$, the HD and CD, and the adjustements to the equilibrium term.

[8]Alternatively, estimation strategies proposed to tighten the dimension of parameters matrix could be used (see among others, Canova and Ciccarelli, 2004; and Canova, 2007; and Sims et al., 2006).

Variable	Coefficient	Std.Error
$ect(-1)$	-0.495**	0.126
$\Delta el(-1)$	-0.012	0.167
$\Delta ip(-1)$	-0.148**	0.066
$\Delta el(-2)$	0.129	0.124
$\Delta ip(-2)$	-0.087*	0.048
$MA12el(-1)$	-0.178*	0.105
$MA12ip(-1)$	0.030	0.037
$d1$	0.031**	0.013
$d2$	-0.040**	0.015
$d3$	0.075**	0.016
$d4$	-0.006	0.019
$d5$	0.062**	0.016
$d6$	0.024	0.023
$d7$	0.035	0.023
$d8$	-0.213**	0.031
$d9$	0.082**	0.045
$d10$	0.176**	0.044
$d11$	0.084**	0.037
ru	0.001	0.004
ly	0.036**	0.013
hd	0.008**	0.004
cd	0.015**	0.006
$const$	-0.050**	0.012

Table 9: **BECM** Final estimates of the states, B_T, and square roots of the corresponding variances for the electricity demand equation; $*$ and $**$ denote significance at the .10 and .05 level, respectively

Variable	Coefficient	Std.Error
$\Delta el(-1)$	-0.207	0.198
$\Delta ip(-1)$	-0.096*	0.054
$\Delta el(-2)$	-0.003	0.147
$\Delta ip(-2)$	-0.022**	0.011
$MA12el(-1)$	-0.263**	0.131
$MA12ip(-1)$	0.021	0.051
$d1$	0.017	0.021
$d2$	-0.067**	0.024
$d3$	0.054**	0.025
$d4$	-0.047	0.031
$d5$	0.055*	0.030
$d6$	0.016	0.037
$d7$	0.013	0.035
$d8$	-0.248*	0.044
$d9$	0.083	0.054
$d10$	0.124**	0.054
$d11$	0.047	0.045
ru	0.002	0.005
ly	0.005	0.026
hd	0.010**	0.005
cd	0.018**	0.009
c	-0.070**	0.023

Table 10: **BVAR** Final estimates of the states, B_T, and square roots of the corresponding variances for the electricity demand equation; $*$ and $**$ denote significance at the .10 and .05 level, respectively

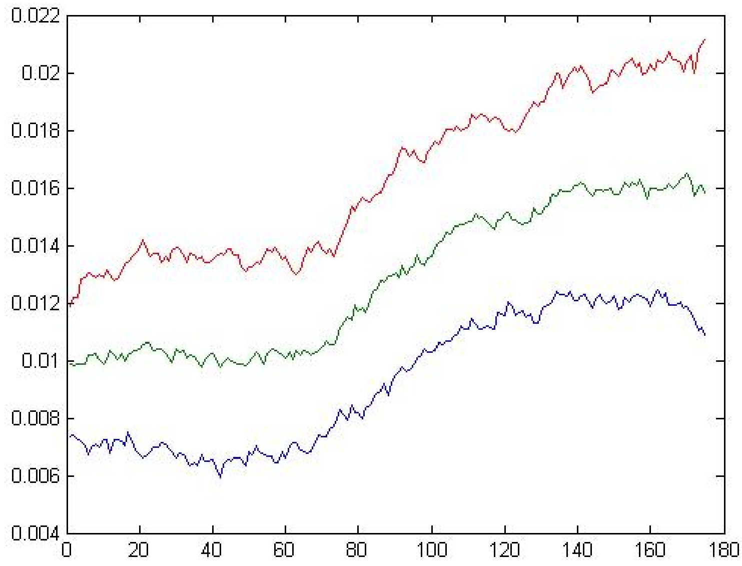


Figure 3: Evolution path of Cooling degree days'(CD) impact on electricity demand growth. TVP BEC model

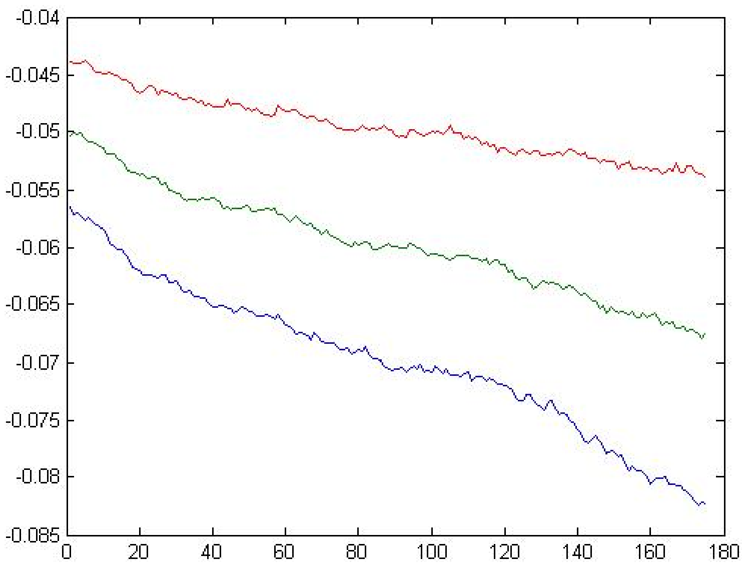


Figure 4: Evolution path of the constant term in the electricity consumption eq of the TVP BECM

As in the unrestricted case, (11) is estimated through the multimove Gibbs sampling technique, a particular variant of MCMC algorithm that allows to draw from the conditional posterior distribution instead of the high dimensional joint posterior of the parameters. In the case in which the parameters are partly constant and partly varying, Gibbs sampling is carried out in four steps, sampling firstly from the posterior of the time-varying parameter, B_t, and in turn from the posterior of the fixed coefficients, Γ, and finally of the precision matrices, H^{ϵ} and H^{η}, conditional on the observed data and the rest of parameters. The final estimates are silmilar to those reported in Table 9 and Table 10, and therefore are not reported.

4 Predictive ability comparison

The models presented in the previous section are now compared based on their predictive ability. The performances are measured by the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE) computed over recursive samples. Relative comparison of forecasts is based on the Diebold Mariano statistic. [9]

The forecasts are made as follows: the first set of forecasts are based on the models estimated through data biginning in January 1990 and ending in December 1999. Using this sample, dynamic predictions are made for the following twelve months. Then the estimation period is extended up to January 2000, and predictions are generated for the next months up to January 2001. This process of adding one year of observatios, re-estimating, and forecasting up to twelve months ahead is repeated until January 2008 has been added to the estimation period . Using this set forecasts, prediction errors are then computed and evaluated in two ways. In tables 11 and 12 the performance of one-month, two-month up to twelve-month ahead predictions is reported. Looking at tables' results, imposing a bayesian prior on the parameters and of allowing them (or a few of them) to vary over time does not seem to lead to a remarkable advantages.[10]

From the figures in Tables 11 and 12 it appears that for one up to two months ahead the univariate model has the largest forecasting accuracy. As the number of forecasted months increases the SARIMA performs badly, whereas forecasts by VECM and by TVP BVAR models are sim-

[9] The parameters of the TVP-BVAR are considered constant for the forecasting period.

[10] These conclusion are not general; however the latter result is somehow supportive of the evidence found by Joutz et al.(1995) using fixed coefficients BVAR for USA data.

ilar, but slightly more accurate in case of VECM. This difference in accuracy diminishes for ten-month up to twelve-month forecasts. To restrict some of the parameters of the TVP BVAR model to be constant over time does not improve model's performance; in fact this leads to slightly worse forecasts.

To conclude about the relative comparison of forecast accuracies the Diebold Mariano statistic is used. Being *di* the loss function associated to model *i* the DM statistic assesses whether the loss differential between the two competitive models differs from zero. The test is given by:

$$S = d/\left(2f_d(0)/T\right)^{.5} \tag{12}$$

where d is the average of loss function differentials and $f_d(0)$ is an estimate of loss differentials' asymptotic variance. The comparison of the VECM vs the BECM and the VECM vs the BVAR model based on the DM statistic are presented in Table 13. The Figures are obtained when the loss function is the RMSE; when the MAE is used the results are very similar and then are not reported.

As expected, the results do not lead to the rejection, at conventional levels, of the hypothesis of equal prediction errors.

Tables 11-13 provide absolute and relative measurements of forecasts accuracy that are based on a large number of repetitions and statistically meaningful. However, economic losses due to various forecasts errors are could not be easy interpretable by comparing statistical measures (e.g. RMSE) or through statistical tests. To give a more immediate view of the costs/benefits associates to the various models, the forecasts in GWh and errors as percentages of the actual values for the years 2007-2009 [11] are reported in Table 14.

Now I consider the last three years and calculate what forecast errors would be made by using the various models to forecast in December the demand over the next year. The results show that the VTP-BECM, which allows for both evolving parameters and adjustment toward the long-run lead level, leads to better economic decisions. For instance, forecasting the demand in 2008 through the TVP-BECM instead of the VECM would eliminate 90% of the error

[11] Yearly forecasts are obtained as sum of monthly figures.

m	SARIMA	VECM	TVP-BECM	TVP-BVAR	PartTVP-BECM	PartTVP-BVAR
1	0.009	0.017	0.026	0.017	0.030	0.017
2	0.015	0.021	0.022	0.021	0.031	0.024
3	0.024	0.023	0.028	0.024	0.037	0.026
4	0.018	0.023	0.032	0.028	0.040	0.029
5	0.030	0.022	0.039	0.032	0.041	0.033
6	0.035	0.024	0.033	0.034	0.041	0.032
7	0.041	0.024	0.041	0.038	0.053	0.037
8	0.051	0.025	0.043	0.039	0.052	0.038
9	0.054	0.028	0.047	0.039	0.053	0.042
10	0.051	0.029	0.043	0.039	0.059	0.043
11	0.061	0.031	0.052	0.039	0.061	0.043
12	0.066	0.033	0.043	0.037	0.054	0.041

Table 11: **RMSE** for electricity demand - Dynamic forecasts over the period $I : 2000.1 - 2000.12 ... XCVIII : 2008.2 - 2009.2$, when the parameter are estimated for $I : 1990.1 - 1999.12 ... XCVIII : 1990.1 - 2008.1$

m	SARIMA	VECM	TVP-BECM	TVP-BVAR	PartTVP-BECM	PartTVP-BVAR
1	0.008	0.014	0.019	0.013	0.021	0.013
2	0.012	0.016	0.016	0.016	0.024	0.018
3	0.018	0.019	0.021	0.020	0.029	0.021
4	0.017	0.019	0.026	0.022	0.032	0.023
5	0.027	0.019	0.030	0.026	0.032	0.027
6	0.032	0.020	0.025	0.028	0.034	0.026
7	0.038	0.020	0.035	0.031	0.043	0.028
8	0.049	0.020	0.037	0.032	0.040	0.033
9	0.053	0.021	0.039	0.032	0.041	0.035
10	0.045	0.022	0.036	0.032	0.049	0.036
11	0.049	0.023	0.045	0.032	0.050	0.036
12	0.052	0.023	0.037	0.030	0.043	0.033

Table 12: **MAE** for electricity demand- see tab:RMSE

with relevant consequences (e.g. for plant management, stock policy, price policies and budget preparation and control). Moreover, the difference in the errors gets larger for 2008 and 2009 because more flexibility allows to better capture the changes in the economic scenario. However, none of the models is able to capture the deep shift of demand in 2009

In what precedes point forecasts have been the object of the analysis. Additional interesting information can be gained from the evaluation of forecast intervals and corresponding empirical coverage rates. A series of 90% forecast intervals (5% and 95% forecast quantiles) are calculated using recursive samples in the same fashion as above described. Then the frequency at which the actual growth rates of demand are contained in the forecast intervals is calculated. In case of the VECM, the distribution of the errors and therefore forecast intervals are obtained by performing the bootstrap over the residual sample; for the Bayesian models they can be derived from the posterior simulation of parameters and variances. In all cases, TVP Bayesian models have higher coverage rates than the classical VECM. The reason relies on the fact that bayesian forecast intervals intrinsecally incorporate parameters' uncertanty. In particular, BECMs with all or part of the coefficients varying display coverage rates close to the desired 90%; TVP-

m	VECM vs TVP-BVAR	VECM vs TVP-BECM	VECM vs PartTVP-BVAR
1	0.427	-0.920	-0.728
2	0.211	0.013	-1.717
3	-0.081	-0.538	-1.372
4	-1.254	-1.169	-1.752
5	-2.409	-1.769	-5.054
6	-1.505	-1.083	-1.296
7	-2.582	-2.792	-1.959
8	-2.313	-3.453	-5.956
9	-1.619	-3.631	-3.332
10	-1.750	-2.912	-1.330
11	-1.327	-6.263	-1.523
12	-1.097	-2.471	-1.425

Table 13: **DM** for electricity demand when the loss function is the RMSE - see tab:RMSE

	VECM	TVP-BECM	TVP-BVAR	PartTVP-BECM	PartTVP-BVAR
2007					
Forecast	344.528	335.750	332.792	331.846	333.548
Prc error	1.4%	-1.2%	-2.1%	-2.4%	-1.9%
2008					
Forecast	347.461	338.700	337.041	340.718	349.871
Prc error	2.4%	-0.2%	-0.7%	0.4%	3.1%
2009					
Forecast	337.598	331.263	334.770	334.512	341.244
Prc error	6.5%	4.5%	5.7%	5.6%	7.7%

Table 14: Demand forecasts for 2007.1:2007.12, 2008.1:2008.12 and 2008.1:2008.12 (TWh), and corresponding percentage errors

	VECM	TVP-BECM	TVP-BVAR	PartTVP-BECM	PartTVP-BVAR
n=1	81%	88%	95%	87%	95%

Table 15: Empirical coverage rates electricity demand growth 90% forecast intervals

BVARs are somehow overcovering, while forecast intervals of the VECM contain the actual growth rates of demand 81% of times only (Table 15).

5 Conclusion

This paper analyses alternative models for forecasting electricity demand. These are a SARIMA specification, a VECM and TVP BVAR models that may or may not include the cointegrating vector among the regressors. The latter specifications seem very appealing, as $i)$ they use all the researcher's information about the coefficients, and $ii)$ they account for possible changes in the parameters over time. Stability analyses show that paramenters vary over time and that they evolve as random walks. Despite this evidence, TVP VARs/TVP BECMs and VECMs show similar forecasting perfomances (as measured by RMSE and MAE). Indeed, to restrict some of the coefficients to be constant over the sample does not improve out-of-sample results. The same evidence is reached when evaluating models' relative forecasting performances by the Diebold-Mariano statistic. In particular, let alone the SARIMA model (which could be preferable for 1-2-step ahead forecasts only) it is not possible to find a model that works clearly better than the others at small, intermediate or large horizons. However, the fixed coefficient VECM performs slightly better for 3-month up to 12-month ahead forecasts, but the differential between the VECM and the TVP-BVAR model tends to reduce for 10-12 step ahead forecasts. For further research, I plan $a)$ to extend the sources of time variability to the variance-covariance matrices of the shocks, and $b)$ to apply a strategy alternative to the one already adopted in the present study to tighten parameters' dimension.

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6 Appendix

Datails of the examined series. Electricity demand data are provided by Terna. Series of the Italian industrial production are published monthly by ISTAT. Also, the two vectors accounting for calendar effects are by ISTAT. The source of the data on Heating and Cooling Degree Days is Bloomberg, and the two series are defined as:

$$CDD = max\,(0, t - 18)$$

$$HDD = max\,(0, 18 - t)$$

where t is the average daily temperature.

Part II

Three-regime Threshold Error Correction Models and the Law of One Price: the Case of European Electricity Markets

Abstract

In this paper threshold error correction models (TVECMs) and min-max (MM) models are applied to examine the integration of European electricity markets. The relationships among EEX, APX, APX-UK and Powernext forward prices are assessed allowing for the possibility that the convergence in prices may not always be operational. Indeed, interdependences may occur only when the spread in prices between two markets makes it profitable to invest in cross-border contracts. As a main result, allowing for non-linear adjustment dynamics improves the accuracy of the model.

1 Introduction

Along with the liberalization of power industry and the introduction of competition, electricity has become a tradable good. In Europe, the reorganization of the electricity market dates back to the 90s, and the process has been driven by the adoption of two European directives that introduced common rules for cross-country transactions to favour the creation of a common power market (Directive 96/92/EC and Directive 2003/54/EC).

As storage of electricity is not economically feasible, cross border exchanges are needed to cope with unbalance of internal consumption and production capacity ensuring the match between demand and supply. Moreover, non-storability gives rise to an increased need for risk management and futures and forward trading.

Efficiency in European spot and forward[1] markets should lead prices to move together in the long run. However, cointegration may not always be operational. This problem may be negligible for spot markets, where in absence of grid congestions neighboring countries' prices are identical.[2] In contrast, heterogeneity of risks and the possibility that future spot prices differ across markets may prevent transactions when the spread in forward prices is too low. Therefore, the difference in prices may need to be sufficiently large for cross-border forward contracts being exchanged, leading to interdependences in prices and adjustment mechanisms. This feature can give rise to a three-regime process, in which it exists a band of non-adjustment, while a pull toward the equilibrium is operational from each outer region.

Moreover, it can be noted that forward contracts are mainly used as hedging instruments and thus cross-border financial contracts are traded only when the physical exchanges of power are also possible. In practice, due to transmission losses and regulation limits, trading is used only between countries that are neighboring or in the same regional market.

Several contributions have dealt with the integration of European prices. However, the majority of them have considered spot markets (an exception is Bunn and Gianfreda, 2009) and linear modelling (see among others Bosco et al., 2009). A non linear model approach based on regime-switching VAR models is introduced by Haldrup and Nielsen (2009) to model spot prices in the Nordic Power market.

[1]In what follows I will use 'forward' to mean both forward and future markets.

[2]In fact, neutral bounds may be associated with transaction and transportation costs related to cross-border spot transactions.

In this paper the relationship between cross-country forward markets is considered. Future spot prices expectations may differ across markets due to diversified production technologies and various degrees of market power coupled with limited transmission capacities. To examine whether a long-run convergence in derivative markets exists, while allowing for the possibility that cointegration may not always hold, TVECMs are used and compared to the results of an MM approach. The empirical findings support the existence of a neutral band inside cointegrated regions. This feature of cross-hedging needs to be considered when it is evaluated to what extent prices adjust to the common equilibrium.

2 Cross Integration in European Electricity Markets

As a part of the liberalization process, various national markets were opened up to cross-border trading by the creation of regional power systems. Besides the establishment of the Nord Pool [3], an agreement between France, Belgium and the Netherlands in 2006 conducted to the creation of a coordinate trading system (TLC - Trilateral Market Coupling); similarly in July 2007 an Iberian electricity market (MIBEL) was created by Spain and Portugal. Another initiative was the creation in October 2008 of a central Auction Office (EMCC) to operate market coupling between Germany and Denmark. While Nord Pool is a single power exchange, the countries in TLC, MIBEL and EMCC have separate markets, but with harmonized design and simplified cross-border exchanges. The creation of regional markets is seen as an intermediate step to the building of the Internal Electricity Market (IEM) as foreseen by the directive 96/92/EC.

The sources of electricity production are rather diversified across countries. For example, in Germany fossil fuelled power plants constitute the price setting technology. In contrast, the electricity production in France is dominated by nuclear energy, which amounts approximately to 78% of total production. Per capita consumption is very heterogeneous across countries either.

When price differentials exist, there are transmissions of energy across countries, when the power grid transmission capacity is adequate to support the flow of electricity. From what stated above, there appear various reasons why the "law of one price" may not be always operational across European power markets:

[3] Nord Pool includes Norway, Sweden, Finland and Denmark and partly Germany, and operates since early 90s

The first intuition is that the "law of one price" could not apply in presence of bottlenecks: physical transmission of electricity across countries is bound by capacity constraints. Therefore, in separated power exchanges (where markets participants trade day ahead power contracts) different prices may prevail depending upon regional demand and supply conditions (see Haldrup and Nielsen, 2009).
Analysing the derivative markets, where long-term contracts are traded to manage the risk of future price levels, it can be observed that the higher the correlation between two markets, the more effective cross-hedging strategies will be. Since sources of production and degrees of market concentration differ across countries, forward prices incorporate different cost expectations [4]. Therefore, foreign forward contracts represent an indirect hedging instrument, and the spread in two countries forward prices needs to be far enough from the equilibrium to induce investors to trade cross-border contracts to hedge risk.
Finally, an open question is whether overall European prices tend to converge, or insufficient networks coupled with market inefficiencies prevent the 'law of one price' to prevail across European countries.
Focusing on the forward market, the main aim of the present paper is to provide an answer to the last question, while controlling for the fact that convergence in prices is possible only for sufficiently large spreads among prices. To this extent, the existence of non-linear cointegration allowing for the possibility of a band of non-adjustment is tested.

3 The econometric framework

In the present paper, three-regime vector error correction models are the basic tool used to model a situation in which the series may or may not be cointegrated depending on how far from the equilibrium relationship they are.
The idea of threshold cointegration has been introduced by the seminal paper of Balke and Fomby (1997). They assume that the cointegrating relationship, instead of being a linear function, follows a threshold autoregressive (TAR) process. The estimation procedure relies on the single equation Engle-Granger approach. Moreover, they use a two-step approach in which

[4] Given the non storability of electricity, future prices are related to fundamental expectations of future spot prices applying a forward premium that is a function of the variance and skewness of current spot prices(see Redl et al., 2009 and Bessembinder and Lemmon, 2002)

cointegration and threshold behaviour are tested separately.
The model has attracted considerable attention (see Lo and Zivot, 2001 for a literature review). A relevant extension of the literature is provided by Hansen and Seo (2002) that propose system estimation and testing methods of the complete multivariate threshold model. Theirs is a two-regime model defined on the equilibrium term being above or below the threshold. In the present study, their settings are modified to allow, coherently with the Balke and Fomby (1997) analysis, for a band of non-adjustment. Finally, a similar threshold cointergration could originate from the integrated min-max (MM) process introduced by Granger and Hyung (2006). Here I consider a partly linearised version of the model and adapt it to the problem at stake.

3.1 The threshold cointegration Balke and Fomby (1997) model

Let $x_{1,t}$ and $x_{2,t}$ be two $I(1)$ series that originate a cointegrated system with the error correction term given by:

$$x_{1,t} + \beta x_{2,t} = z_t \tag{1}$$

Balke and Fomby (1997) define the residuals of the above relation as:

$$z_t = \rho^{(i)} z_{t-1} + \epsilon_t \tag{2}$$

where ρ equals 1 if $r_1 < z_{t-1} \leq r_2$ and $|\rho| < 1$ if $z_{t-1} \leq r_1$ or $z_{t-1} > r_2$.
Since the β does not vary according to the regimes, the above model can be equivalently expressed in VECM form:

$$\begin{aligned}
\Delta x_{1,t} &= \mu_1^{(i)} + \lambda_1^{(i)} z_{t-1} + \sum_{j=1}^{p-1} \bar{\delta}_{1,j} \Delta x_{t-j} + \zeta_{x1,t} \\
\Delta x_{2,t} &= \mu_2^{(i)} + \lambda_2^{(i)} z_{t-1} + \sum_{j=1}^{p-1} \bar{\delta}_{2,j} \Delta x_{t-j} + \zeta_{x2,t}
\end{aligned} \tag{3}$$

where

$$\mu_m^{(i)} = \begin{cases} \mu_{m,1} & \text{if } z_{t-1} \leq r_1 \\ 0 & \text{if } r_1 < z_{t-1} \leq r_2 \\ \mu_{m,2} & \text{if } z_{t-1} > r_2 \end{cases}$$

$$\lambda_m^{(i)} = \begin{cases} \lambda_{m,1} & \text{if } z_{t-1} \le r_1 \\ 0 & \text{if } r_1 < z_{t-1} \le r_2 \\ \lambda_{m,2} & \text{if } z_{t-1} > r_2 \end{cases}$$

with $x_t = (x_{1,t}, x_{2,t})$ and $m = 1, 2$. Estimates of the model are obtained using conditional least squares. The support for the threshold variables is defined as $[z_L, z_U]$, where z_L ans z_U are respectively the lower and the upper values that the threshold can take, and are such that $\pi_0 \le P(z_{t-1} \le z_L)$ and $P(z_{t-1} \le z_U) \le 1 - \pi_0$. In empirical applications setting π_0 between .05 and .15 has resulted to be opportune.

3.2 The threshold cointegration Hansen and Seo (2002) VECM

Differntly from Balke and Fomby (1997), Hansen and Seo (2002) consider a p-dimentional $I(1)$ time series x_t that is cointegrated with still only one $p \times 1$ cointegrating vector β. The extension of (3) to a multivatiare system takes the form:

$$\Delta x_t = A_1^{'} X_{t-1}(\beta) d_{1,t}(\beta, \gamma) + A_2^{'} X_{t-1}(\beta) d_{2,t}(\beta, \gamma) + e_t \tag{4}$$

where

$$\begin{aligned} d_{1,t}(\beta, \gamma) &= 1(z_{t-1}(\beta) \le \gamma) \\ d_{2,t}(\beta, \gamma) &= 1(z_{t-1}(\beta) > \gamma) \end{aligned} \tag{5}$$

and $X_{t-1} = (1 \quad z_{t-1}(\beta) \quad \Delta x_{t-1} \quad \ldots \quad \Delta x_{t-p+1})'$.

To estimate 4 they propose to firstly execute a grid-search over the two dimensional space (β, γ). The empirical support for the threshold γ is defined as described above. The search region for the β is given by $[\beta_L, \beta_U]$ and is constructed over a large inteval of β (such as the asymptotic normal approximation). Parameters estimates are obtained by constrained maximum likelihood estimation. In practice:

i) Letting fixed (β, γ) for each possible value of their supports, the conditional MLE of (A_1, A_2, Σ) is obtained;

ii) The estimates of β and γ are obtained as those that minimize the negative likelihood of the model;

iii) $(\hat{A}_1, \hat{A}_2, \hat{\Sigma})$ are the estimated values corresponding to the $\hat{\beta}$ and $\hat{\gamma}$.

In specification (5) one price adjustment process applies if the deviations from the long-term equilibrium are below a threshold (regime 1) and another applies if the opposite is true (regime 2). Such a specification excludes the possibility of a "band of non-adjustment" of smaller deviations from a long-term equilibrium inside a regime of adjustment to bigger deviations. In this paper a more meaningful specification for the problem in question is implemented. The settings of Hansen and Seo (2002) are slightly modified by substituting 5 with:

$$
\begin{aligned}
&d_{1,t}(\beta, \gamma) = 1(|z_{t-1}(\beta)| \leq \gamma) \\
&d_{2,t}(\beta, \gamma) = 1(|z_{t-1}(\beta)| > \gamma)
\end{aligned}
\tag{6}
$$

In (6) it is assumed, in line with the three-regime model of Balke and Fomby (1997), that one regime holds when absolute deviations from the long-term equilibrium are smaller than the threshold (regime 1) and another for errors that are larger in absolute values(regime 2). The model in (4) and (6) is a restricted version of a general three-regime threshold model, where $\gamma_1 = -\gamma_2$ so that no asymmetric price transmission is possible in (6), and the same price reaction occurs regardless of whether spread in prices is positive or negative[5].

To test the existence of threshold cointegration instead of linear cointegration I use the multivariate procedure proposed by HS. Given γ and β the VECM and TVECM are linear. As the former model is a special case of the latter, a LM-like statistic that is robust to heteroskedasticity can be used. Formally, the test statistic can be expressed as:

$$
\begin{aligned}
LM(\beta, \gamma) \quad &= vec\left(\hat{A}_1(\beta, \gamma) - \hat{A}_2(\beta, \gamma)\right)' \left(\hat{V}_1(\beta, \gamma) + \hat{V}_2(\beta, \gamma)\right)^{-1} \\
&\qquad \times vec\left(\hat{A}_1(\beta, \gamma) - \hat{A}_2(\beta, \gamma)\right)
\end{aligned}
\tag{7}
$$

where vec is the vec operator, $\hat{A}_i(\beta, \gamma)$ are parameters estimates and $\hat{V}_i(\beta, \gamma)$ the corresponding Eicker-White covariance matrices. The LM statistic 7 is evaluated at point estimates obtained under H_0. Let the null estimate of β being $\tilde{\beta}$. The threshold γ is not defined under the null of

[5]In fact, the advantage of easy interpretable results from a two-threshold error correction model is weakened by the fact that un to my knowledge no adequate econometric test for the significance of two thresholds has been developed (see Hansen and Seo, 2002)

linearity, therefore the proposed statistic is:

$$SupLM = supLM(\tilde{\beta}, \gamma) \tag{8}$$

where the sup is with respect to γ, the search region is $[\gamma_L, \gamma_U]$ and $\tilde{\beta}$ is the linear VECM estimate of β.

To obtain the critical values and the p-values corresponding to the estimated statistic the residual bootstrap is applied. The parameters' estimates and the residuals series obtained under the null (linear VECM) are used for initializating the algorithm. The bootstrap distribution is calculated by randomly drowing from the residuals and creating new vector series x_b. The statistic supLM is calculated on each simulated sample and stored. The bootstrap p-value is the percentage of simulated statististics that exceed the actual statistic.

3.3 The MM process

The integrated Min-Max process is given by the bivariate system:

$$x_{1,t+1} = max\,(x_{1,t} + a, x_{2,t} + b) + \epsilon_{1,t+1} \tag{9}$$

$$x_{2,t+1} = min\,(x_{1,t} + c, x_{2,t} + d) + \epsilon_{2,t+1} \tag{10}$$

As it is shown by Granger and Hyung (2006) the two series above may be cointegrated even if they are two non-linearly integrated processes. Moreover, $a - d < 0$ is a sufficient condition for an equillibrium to exist. If instead of using a max-min pair, the min operator is linearized the same sufficient condition holds. Assuming that the cointegration equation is given and equal to $[1, -1]$ and definying $z_t = x_{1,t} - x_{2,t}$ the partially linearized model constitute a VECM system having:

$$\Delta x_{1,t+1} \quad = max\,(a, b - z_t) + \epsilon_{1,t+1} \tag{11}$$

$$\Delta x_{2,t+1} \qquad = d + \epsilon_{2,t+1} \tag{12}$$

and gives rise to:

- Region(I): if $z_t \geq b - a$ then $z_{t+1} = a - d + z_t + \eta_{t+1}$, so that z_t is $I(1)$ in this region

- Region(II): if $z_t < b - a$ then $z_{t+1} = b - d + \eta_{t+1}$, so that z_t is $I(0)$.

Granger and Hyung (2006) apply the above process to analyse one risky interest rate and one risk-free rate, and their spread. While the latter is always positive, the equilibrium term between cross-country electricity prices may be positive in some periods and negative in others, which leads to opposite minimizing and maximizing behaviours. To take this fact explicitly into account (11)-(12) can be modified as:

$$\begin{aligned} \Delta x_{1,t+1} &= min\,(a^+, b^+ - z_t)\,1\,(z_t > 0) + max\,(a^-, b^- - z_t)1\,(z_t \leq 0) + \epsilon_{1,t+1} \\ \Delta x_{2,t+1} &= d + \epsilon_{2,t+1} \end{aligned} \tag{13}$$

By subtracting Δy_{t+1} from Δx_{t+1} and using $min(-X, -Y) = -max(X, Y)$, it is obtained that:
$\Delta z_{t+1} = ((a^+ - d^+) - max\,(0, z_t - b^+ + a^+))\,1\,(z_t > 0) +$
$+\,((a^- - d^-) + max\,(0, b^- - a^- - z_t))\,1\,(z_t \leq 0)$ (13)
The adjustment mechanisms in 3.3 is illustrated in Figure 1 in the Appendix.

4 Data analysis

The data used in this paper are (logs of) baseload week-ahead electricity prices for the power exchange of the United Kingdom (UK), Germany (GE), France (FR) and the Netherlands (NE); the observations are daily records. The data set covers the period June 2005 - September 2009; for Germany the sample period starts in September 2007. The data series are displayed in Figure 3 and are reported in the Appendix.

As it can be noted, typical features of electricity prices include pronounced volatility and spikes. In this paper I do not try to average out abrupt changes, since extreme movements can contribute to make threshold models opportune to analyze electricity prices.

ADF test statistics [6] document that the log-transformed series are I(1) at the 5% level, except for French prices, where the null of unit root is not-rejected at the 1% level only. It should be noted, however, that the performed ADF tests do not allow for threshold behavior. The results are reported in Table 1.[7]

[6] The lag order in the auxiliary regression has been chosen by minimizing the BIC.

[7] Others find different results on the long memory properties of electricity prices (e.g. Haldrup and Nielsen, 2009 find prices in the Nord Pool being fractionally integrated).

The visual inspection of the series can give useful information about series patterns. Figure 4 in the Appendix reports the scatter plots for each couple of log-prices.
To conclude the analysis of the data, the correlations between prices in pairs are reported. Since the figures Table 2 may have problems of spurious correlation, the correlations are calculated also for growth rates (Table 3).
The highest correlation in grow rates is between GE and FR. However, these are simple deterministic statistics and fuller interpretation requires the models to be estimated below.

5 Empirical Results

The plots in Figure 4 above show two main features:

1. The largest amount of points can be observed around a line at approximately $45°$ slope;

2. Some observations are spread elsewhere in the graphs.

Based on the first remark, a VECM seems to be a reasonable tool for analyzing the dynamics of the series and estimating the long run relationship between the prices. Efficiency in the market would imply the slope of the equilibrium relationship to be one. Whether the estimated slope of the equilibrium relationship is not significantly different from that theoretical value can then be tested.

The second observation suggests that a TVECM may be a more appropriate tool in that it allows for the possibility that the speeds of adjustment toward the equilibrium (or the existence of a

Variable	UK	GE	NE	FR
ADF	-2.569	2.638	-2.737	-3.343*

Table 1: **ADF test statistic** - case with intercept; the relevant critical values are -2.868 and -3.447 at the 5% and 1% levels, respectively; $*$ denotes significance at the 5% level but not at the 1%.

	UK	GE	NE	FR
UK	1.000			
GE	.856	1.000		
NE	.847	.933	1.000	
FR	.821	.928	.872	1.000

Table 2: **Correlations**

	UK	GE	NE	FR
UK	1.000			
GE	.100	1.000		
NE	.115	.236	1.000	
FR	.215	.635	.189	1.000

Table 3: **Growth rates correlations**

cointegrating relationship) differ for data points close to the $45°$ line and observations spread farther away in the graph.

In what follows the estimates of VECM and TVECM are reported. For each pair of prices the integration level between the markets can be evaluated; moreover the results can be compared across different pairs.
For all estimations, the Eicker-White heteroskedasticity robust standard errors are reported in brackets, and the lag order has been fixed at one. In the TVECM the cointegrating vector is the threshold variable that determines the switch from the non-adjustment regime to the cointegrated one and viceversa. The inaction corridor is defined symmetrically and spans between $-\gamma$ and $+\gamma$. In practice, it is likely that country A's investors undertake cross-border forward trading with country B only when the ratio beetween the two (weighted) prices is large enough to exceed the differences in risks.[8] Formally, let F_A and F_B be the two forward prices, $|log\left(F_A/F_B^{\beta}\right)| \leq \gamma$ defines region 1 (neutral state), and $|log\left(F_A/F_B^{\beta}\right)| > \gamma$ the other

[8]For a more complete description of cross-hedging of electricity see among others Woo et al. (2001).

one. So one gets that the inaction region is defined as:

$$F_A/F_B^{\beta} \geq \exp(-\gamma)\text{if}log\left(F_A/F_B^{\beta}\right) < 0$$
$$F_A/F_B^{\beta} \leq \exp(\gamma)\text{if}log\left(F_A/F_B^{\beta}\right) > 0 \tag{14}$$
$$\tag{15}$$

For the threshold models, the two dimensional grid search is performed as described above and the number of grid points for both, β and γ, parameters is set to 300. The non linear estimates of the cointegrating and the threshold coefficients, $(\hat{\beta}, \hat{\gamma})$ are obtained by minimizing the Negative Log-likelihood. For all estimated model, in Figure 6 in the Appendix the equilibrium terms are reported by splitting data points in regime 1 and in regime 2.

5.1 The UK -France

Electricity forward contracts are traded in the financial markets and generally do not imply physical exchanges. Nevertheless, the cross-border hedging stragies are eventually influenced by the possibility of physical exchanges of energy. Therefore the existence of a direct interconnection between the British and French power markets may matters for the results. Table 4 reports the estimates of the models.

The estimate of the threshold is $\hat{\gamma} = .351$ (i.e. $.704$ and 1.420 define the bounds for the ratio of the weighted prices). The estimated cointegrated coefficients are $\tilde{\beta} = 1.158$ and $\hat{\beta} = 1.059$ for the VECM and TVECM, respectively. The latter value is numerically close to 1. Whether $\tilde{\beta}$ significantly differs from 1 can be tested (Johansen, 1995). The equilibrium term is inside the bounds the 91% of times, and outside the 'non-adjustment' corridor in the remaining 9% of cases. These percentages are expected as the prices difference should be virtually null in absence of events s.a. relevant maintenance operations or new regulated prices in a market. How the observations switch from one regime to the other (due to the equilibrium relationship in absolute values being below or above $\hat{\gamma}$) is shown in Figure 6. Outside the bounds the adjustment coefficient of the first equation (UK) is significant. In the remaining cases the loadings are insignificant or numerically very small. Indeed, the wald test for the equality of adjustment coefficients reject the null. The Wald test for the dynamic component is insignificant.

	$VECM$	$TVECM$	
β	1.158 (0.076)	1.059	
γ		0.351	
		$REGIME1$ 90.5prc	$REGIME2$ 9.5prc
	Equation1		
λ	-0.045 (0.013)	-0.024 (0.014)	-0.141 (0.041)
μ	-0.023 (0.007)	-0.001 (0.002)	-0.057 (0.020)
$\delta 1$	0.053 (0.047)	0.037 (0.056)	0.198 (0.066)
$\delta 2$	0.004 (0.031)	0.020 (0.034)	-0.012 (0.074)
	Equation2		
λ	0.075 (0.019)	0.054 (0.018)	0.067 (0.043)
μ	0.037 (0.009)	0.009 (0.003)	-0.022 (0.017)
$\delta 1$	0.101 (0.039)	0.069 (0.037)	0.267 (0.113)
$\delta 2$	-0.019 (0.036)	-0.029 (0.032)	0.096 (0.140)
W_{Dyn}		7.230 [.124]	
W_{ECM}		8.861 [.012]	
$NLogL$	-4916.009	-4938.312	
AIC	-4900.009	-4906.312	
BIC	-4892.246	-4890.786	

Table 4: **U-F estimates**; the Eicker - White S.E. are reported in round brackets; p-values for the Wald tests are in square brackets

5.2 Germany - The Netherlands

As UK and France, Germany and the Netherlands are interconnected markets, whith a volume of exchanges that largely exceeds the previous case. The results for this couple of (log-)prices is reported in Table 5.
The estimated threshold value is $\hat{\gamma} = .248$ (i.e. .780 and 1.281 are the bounds for $F_{GE}/F_{NE}^{\hat{\beta}}$), which is lower than the .35 estimated in case of UK and France. This seems to reflect the higher level of interconnection of the between Germany and the Netherlands than for UK- France.

	$VECM$	$TVECM$	
β	0.944 (0.032)	0.968	
γ		0.248	
		$REGIME1$ 94.85prc	$REGIME2$ 5.1prc
	Equation1		
λ	-0.085 (0.049)	-0.045 (0.076)	-0.001 (0.043)
μ	0.016 (0.010)	0.007 (0.008)	-0.041 (0.017)
$\delta 1$	0.003 (0.056)	0.122 (0.048)	-0.134 (0.093)
$\delta 2$	0.042 (0.044)	0.003 (0.042)	-14.362 (2.446)
	Equation2		
λ	0.290 (0.086)	0.135 (0.036)	0.534 (0.101)
μ	-0.052 (0.016)	-0.010 (0.004)	-0.084 (0.025)
$\delta 1$	-0.096 (0.081)	0.132 (0.050)	-0.502 (0.142)
$\delta 2$	0.014 (0.043)	-0.033 (0.031)	1.980 (1.983)
W_{Dyn}		104.725 [.000]	
W_{Dyn}		13.948 [.001]	
NLogL	-2647.111	-2702.121	
AIC	-2631.046	-2670.121	
BIC	-2625.617	-2625.618	

Table 5: **G-N estimates**; the Eicker - White S.E. are reported in round brackets; p-values for the Wald tests are in square brackets

The estimated cointegrating vector is $\hat{\beta} = .968$, and in the linear case, $\tilde{\beta}$=.944. Similar to the Uk - France case, over the 94% of times the two prices are close, while in the remaining 5% of cases the error toward the equilibrium exceeds the bounds. The adjustment coefficients are either small or non significant in Regime 1. In the second regime the loading of the Nederlands equation gets larger. Strangely one dymanic parameter of the first equation becomes very large. However, the dymanic part of the TVECM is imprecisely estimated, because of the small number of observations in the second regime.

5.3 Germany - France

Germany and France are well interconnected markets and the volume of exchanges between these platforms lead to significant links between the two markets. Table **G-F** reports the estimates.

	$VECM$	$TVECM$	
β	0.887 (0.057)	0.982	
γ		0.244	
		$REGIME1$ 94.99prc	$REGIME2$ 5.02prc
	Equation 1		
λ	-0.103 (0.071)	0.023 (0.044)	-0.641 (0.181)
μ	0.041 (0.030)	0.001 (0.003)	-0.165 (0.047)
$\delta 1$	-0.086 (0.077)	0.024 (0.061)	0.528 (0.299)
$\delta 2$	0.139 (0.077)	0.119 (0.073)	-0.577 (0.298)
	Equation 2		
λ	0.046 (0.062)	0.117 (0.048)	-0.235 (0.148)
μ	-0.018 (0.003)	-0.003 (0.003)	-0.053 (0.047)
$\delta 1$	0.160 (0.082)	0.087 (0.052)	0.722 (0.291)
$\delta 2$	-0.031 (0.073)	0.087 (0.054)	-0.705 (0.293)
W_{Dyn}		14.478 [.006]	
W_{ECM}		15.673 [.000]	
NLogL	-2737.046	-2782.333	
AIC	-2721.046	-2750.333	
BIC	-2715.461	-2739.163	

Table 6: **G-F estimates**; the Eicker - White S.E. are reported in round brackets; p-values for the Wald tests are in square brackets

The point estimates of the cointegrating coefficients are $\tilde{\beta} = .887$ (which is not statistically different from 1) in case of the linear model, and $\hat{\beta} = .981$ for the threshold one. The threshold $\hat{\gamma} = .244$ is numerically close to the one estimated for the Germany - Netherlands case and

$\exp(\hat{\pm\gamma}) = .7831$ and 1.276. Non-adjustment state dominates the pooled data set ($|z_{t-1}| \leq \hat{\gamma}$ 95 $\%$ of times). In the first regime the loading of the France equation is significant. In contrast, in regime 2 only Germany appears to adjust toward the equilibrium. Moreover in that regime the loading of the second equation, although not signficant at the 5% level, is negative. I would have expected it to be positive. When $log(F_{GE}) - \beta log(F_{FR})$ is large one would expect F_{FR} to rise. By omitting the threshold and estimating a VECM the loadings are not significant.

5.4 The UK - The Netherlands

The value $\tilde{\beta}$ is significantly larger than 1, and $\hat{\beta}$=1.30. The estimated threshold is $\hat{\gamma} = .988$, which is mutch larger than estimated threshold for the previous pairs of prices. Despite the large threshold, the first regime holds 24% of times only. In regime 1, point estimates of the loading and the constant term of the first equation are strangely large, while they are insignificant for the second equation. In the second regime loadings and intercepts are significant but small. The Wald statistics suggest significant differences between the coefficients in the two states.

5.5 The Netherlands - France

In this case, the estimated γ is very small, which may be what leads the first state to hold 7% of times. Moreover, loadings estimates suggest that the adjustment toward the equilibrium applies only inside the bounds, which contrasts with the expectations.

5.6 The UK - Germany

For these two markets, the estimated γ is big and $\tilde{\beta}$ and $\hat{\beta}$ are far from one. In regime 1 the loadings and the intercepts of the second equation are significant but the point estimates are very small. In the second regime the adjustment is not significant in case of the UK equations while it is significant and big for Germany. Wald tests do not evidence asymmetries neither in the dynamic nor in the error correction coefficients.

Overall the estimated models appear to be appropriate for capturing the integration across EU prices and the possible non-linearities in the adjustment process. The evidence found using the

	$VECM$	$TVECM$	
β	1.221 (0.084)	1.300	
γ		.988	
		$REGIME1$ 23.62prc	$REGIME2$ 76.38prc
	Equation1		
λ	-0.058 (0.017)	-0.392 (0.102)	-0.053 (0.018)
μ	-0.049 (0.015)	-0.360 (0.094)	-0.064 (0.022)
$\delta 1$	0.074 (0.049)	0.244 (0.090)	0.034 (0.057)
$\delta 2$	0.013 (0.040)	-0.137 (0.099)	0.047 (0.037)
	Equation2		
λ	0.070 (0.019)	0.077 (0.060)	0.098 (0.030)
μ	0.059 (0.015)	0.077 (0.055)	0.116 (0.036)
$\delta 1$	0.082 (0.052)	0.083 (0.042)	0.079 (0.077)
$\delta 2$	-0.053 (0.063)	-0.343 (0.135)	0.049 (0.036)
W_{Dyn}		11.553 [.021]	
W_{ECM}		11.178 [.003]	
NLogL	-4037.665	-4065.967	
AIC	-4021.665	-4033.967	
BIC	-4014.610	-4019.855	

Table 7: **U-N estimates**;the Eicker - White S.E. are reported in round brackets; p-values for the Wald tests are in square brackets

threshold models suggests that week ahead forward markets are more integrated in case the considered markets are neighbouring markets. When compared based on the AIC and the BIC, the threshodl model exibits a better performance than the VECM for all the considered pairs of prices.

	$VECM$	$TVECM$	
β	0.913 (0.058)	0.957	
γ		0.074	
		$REGIME1$ 7.174 prc	$REGIME2$ 92.82prc
	Equation1		
λ	-0.080 (0.024)	-0.107 (0.200)	-0.068 (0.026)
μ	0.032 (0.010)	0.019 (0.010)	0.014 (0.006)
$\delta 1$	-0.032 (0.029)	-0.029 (0.062)	-0.054 (0.033)
$\delta 2$	0.120 (0.039)	0.453 (0.111)	0.089 (0.041)
	Equation2		
λ	0.069 (0.023)	1.351 (0.566)	0.051 (0.021)
μ	-0.028 (0.010)	-0.072 (0.029)	-0.011 (0.006)
$\delta 1$	0.007 (0.048)	0.008 (0.212)	0.010 (0.040)
$\delta 2$	-0.010 (0.038)	0.265 (0.236)	-0.020 (0.033)
W_{Dyn}		13.516 [.009]	
W_{ECM}		7.108 [.028]	
NLogL	-4742.967	-4771.906	
AIC	-4726.967	-4739.906	
BIC	-4729.309	-4724.592	

Table 8: **N-F estimates**; the Eicker - White S.E. are reported in round brackets; p-values for the Wald tests are in square brackets

6 Testing for threshold

The hypothesis of linear VECM against the threshold one is tested using the multivariate supLM statistic of Hansen and Seo (2002) as above described.
The results of the test statistics are reported in the table 10 that follows. The empirical distribution of the statistic is obtained by residual bootstrap, and the number of simulations is set to 5000. The figures show that the supLM statistic is significant at the 10% level only for Germany - France, The Netherlands - France and The Uk - Germany pairs of prices.

	$VECM$	$TVECM$	
β	1.350 (.093)	1.252	
γ		1.049	
		$REGIME1$ 93.62prc	$REGIME2$ 6.38prc
	Equation1		
λ	-0.040 (0.015)	-0.022 (0.017)	0.129 (0.132)
μ	-0.049 (0.018)	-0.020 (0.014)	0.201 (0.166)
$\delta 1$	-0.002 (0.014)	-0.009 (0.015)	0.011 (0.324)
$\delta 2$	0.038 (0.041)	0.070 (0.054)	-0.046 (0.074)
	Equation2		
λ	0.095 (0.029)	0.072 (0.034)	0.433 (0.203)
μ	0.114 (0.034)	0.061 (0.027)	0.460 (0.234)
$\delta 1$	0.064 (0.049)	0.034 (0.046)	1.364 (0.856)
$\delta 2$	0.023 (0.051)	0.081 (0.041)	-0.035 (0.165)
W_{Dyn}		6.472 [.167]	
W_{ECM}		4.107 [.128]	
NLogL	-2752.992	-2775.507	
AIC	-2736.992	-2743.507	
BIC	-2731.499	-2732.520	

Table 9: **U-G estimates**; the Eicker - White S.E. are reported in round brackets; p-values for the Wald tests are in square brackets

	UK-FR	GE-NE	GE-FR	UK-NE	NE-FR	UK-GE
$supLM$	17.470	15.537	18.755	18.296	22.289	16.851
$crit-val$	21.197	19.280	19.462	20.556	21.233	18.054
$p-val$	.191	.235	.065	.114	.034	.082

Table 10: **supLM**

7 Robustness of the results: evidence from the MM model

In this section, it is verified whether the evidence found through Hansen and Seo's model is consistent with the results of an alternative approach, Granger and Hyung's LinMM model, which considers explicitly the minimizing and maximizing behaviors of economic agents. Moreover, I modify the specification proposed by the authors to take into account the opposite minimizing and maximizing behaviors that the agents will show when the equilibrium is positive or negative. The model is defined in (13) with $z_t = x_t - \beta y_t$, but with β estimated instead of being fixed at one[9]. Coherently with this framework, in case of positive z_t the system gives rise to two regions:

- RIp. z_{t+1} is a RW with drift $a^+ - d^+$ if $z_t < b^+ - a^+$ and

- RIIp. z_{t+1} is stationary if $z_t > b^+ - a^+$.

For negative z_t, two other regions arise:

- RIn. z_{t+1} is a RW with drift $a^- - d^-$ if $z_t > b^- - a^-$ and

- RIIn. z_{t+1} is $I(0)$ if $z_t < b^- - a^-$.

Overall, the system gives rise to an inaction band for small (weighted) differences between prices inside an upper and a lower cointegrated regions. Differently from the estimated TVECM, the LinMM is specified in such a way to allow for the thresholds and drifts to vary when the equilibrium term is positive or negative. Tables 11-16 summarize the estimates of the long-run coefficients for all pairs of prices.

The evidence found shows that the drift terms, $a^+ - d^+$ ($a^- - d^-$),in general are close to zero but negative (positive) in case $z_t > 0$ ($z_t < 0$). This implies that if z_t is in the neutral state it tends to stay there unless the error term is sufficiently large to bring the process outside the bounds.

[9]The two-step approach of Engle and Granger is used for estimating β. Note that the estimated equilibrium terms differ from those obtained in the TVECM case by ML.

	linMMmodel	
	$z_t > 0$	$z_t \leq 0$
	$z_t > b - a$ .9%	$z_t < b - a$ .4%
a	-0.004 (0.003)	0.004 (0.003)
b	0.677 (0.050)	-0.727 (0.073)
d	0.013 (0.003)	-0.011 (0.003)
NLogL	-4908.577	
AIC	-4897.577	
BIC	-4896.367	

Table 11: **Linearized MM model estimates - UF**

	linMMmodel	
	$z_t > 0$	$z_t \leq 0$
	$z_t > b - a$ 2.2%	$z_t < b - a$ .0%
a	0.010 (0.005)	0.000 (0.006)
b	0.348 (0.039)	-0.964 (0.334)
d	0.011 (0.002)	-0.016 (0.003)
NLogL	-2603.229	
AIC	-2592.229	
BIC	-2591.019	

Table 12: **Linearized MM model estimates - GN**

Indeed, the percentages of observations in the cointegrated regimes (i.e. such that $z_t > b - a$ in case z_t is positive and $z_t < b - a$ for negative z_t) are much lower than those estimated through the previous model.

The figures reported in Tables 11 - 16 support the assumption of symmetric thresholds (b-a) for UK-FR and NE-FR pairs. Point estimates of the bound for $z_t > 0$ in case of GE-NE and GE-FR are close to TVECM estimates. For UK-NE and UK-GE point estimates of b in the positive and negative cases, respectively, are very large. These may be imprecise estimates and reflect

	linMMmodel	
	$z_t > 0$	$z_t \leq 0$
	$z_t > b - a$ 2.2%	$z_t < b - a$ 1.1%
a	0.023 (0.008)	-0.007 (0.009)
b	0.235 (0.033)	-0.416 (0.065)
d	0.005 (0.002)	-0.009 (0.004)
NLogL	-2767.100	
AIC	-2756.100	
BIC	-2754.889	

Table 13: **Linearized MM model estimates - GF**

	linMMmodel	
	$z_t > 0$	$z_t \leq 0$
	$z_t > b - a$ 2.6%	$z_t < b - a$ .0%
a	0.002 (0.004)	-0.063 (0.026)
b	0.507 (0.031)	-2.895 (0.370)
d	0.005 (0.002)	-0.009 (0.003)
NLogL	-4044.501	
AIC	-4033.501	
BIC	-4032.290	

Table 14: **Linearized MM model estimates - UN**

problems of convergence. Overall, results of the Lin MM model suggest the existence of a neutral regime. However, based on model's estimates, cointegration is rarely active.

8 Conclusion

In this paper I have proposed to use bivariate TVECMs for analysing the convergences in pairs of forward prices across British, German, Dutch and French electricity markets. The use of

	linMMmodel	
	$z_t > 0$	$z_t \leq 0$
	$z_t > b - a$ 1%	$z_t < b - a$ .4%
a	-0.006 (0.003)	0.003 (0.003)
b	0.738 (0.053)	-0.648 (0.050)
d	0.007 (0.002)	-0.006 (0.003)
NLogL	-4731.530	
AIC	-4720.530	
BIC	-4719.320	

Table 15: **Linearized MM model estimates - NF**

	linMMmodel	
	$z_t > 0$	$z_t \leq 0$
	$z_t > b - a$ .0%	$z_t < b - a$ .0%
a	0.004 (0.019)	0.001 (0.003)
b	3.389 (0.466)	-0.577 (0.072)
d	0.012 (0.004)	-0.009 (0.004)
NLogL	-2742.931	
AIC	-2731.931	
BIC	-2730.720	

Table 16: **Linearized MM model estimates - UG**

threshold models is motivated by the expectation that adjustments toward the equilibrium may operate only when the (weighted) differences in prices exceed possible transaction costs and differences in the expected risks associated with different hedging strategies. When the domestic market of one country is affected by some shocks (e.g. unforseen plants' stops or new regulations of prices being approved), the prices may depart from the equilibrium level. This deviations may make it convenient investing in cross-border forward contracts (in general coupled with investments in hedging instruments against the variability of transportation costs). This practice can induce interdependencies in prices and adjustment mechanisms. From the empirical analysis using TVECMs à la Hansen and Seo it appears that conditioning on the absolute values of the errors toward the equilibrium helps to capture the dynamics of cross-border forward trading, and it contributes to examine price convergences appropriately. Out of the six couples of prices analysed, the estimates support the theoretical assumption in four cases, i.e. for the dynamics of the UK - France, Germany - the Netherlands, Germany - France and the Uk - Germany prices. However, the SupLM statistic for the existence of a threshold is significant in three cases only, namely Germany - France, the Netherlands - France and the UK - Germany. The evidence found using the LinMM model of Granger and Hyung confirms the existence of a band of non-adjustment. In fact, the percentages of data points in the cointegrated regimes are much smaller than for the TVECM (and null in one out of six cases), which suggests that cointegration is rarely active. When compared based on the Akaike Information Criteria, TVECMs perform better than the VECMs and the LinMMs in all but the GF case. For further research I would like to allow for the possibility of asymmetric thresholds also in the TVECM à la Hansen and Seo and for the chance that the thresholds vary over the seasons.

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9 Appendix

9.1 Small sample performance

Monte Carlo simulation experiments are performed to verify the convergence of algorithms for the TVECM and the LinMM model for $n = 250$ and 1000 replications.

9.1.1 Small sample performance of TVECM

The data generating process is:

equation $\Delta x_t = \begin{pmatrix} -.2 \\ +.3 \end{pmatrix} (x_{1,t} - \beta_0 x_{2,t})\, 1\,(x_{1,t} - \beta_0 x_{2,t} > \gamma_0) + e_t$

with e_t i.i.d. Normal$(0, I_2)$. The cointegrating coefficient, β_0, and the threshold value, γ_0, are set at 1. The results are reported in Table 17. The results show that β has an approximately

n=250	MEAN	RMSE	MAE	Percentiles				
				5	25	50	75	95
$\beta - \beta_0$	.003	.058	.039	-0.088	-0.023	0.001	0.029	0.102
$\gamma - \gamma_0$	-.117	.790	.610	-1.000	-0.775	-0.319	0.197	1.689

Table 17: **Distribution of estimators** - The estimators $\hat{\beta}$ and $\hat{\gamma}$ are unrestricted estimators obtained as described in Section 2.

symmetric and unbiased distribution; in contrast, the estimator of γ has an asymmetric and quite inaccurate distribution. Overall the results confirm convergence of the algorithm.

9.1.2 Small sample performance of LinMM model

To simulate a Lin MM model the following process is generated:

$$\begin{aligned} \Delta x_{1,t+1} &= min(.02, -z_t + .6) - .06\Delta x_{1,t} + .2x_{2,t}1(z_t > 0) + \\ &\quad +max(-.2, -z_t - .9) - .02\Delta x_{1,t} + .04\Delta x_{2,t} + u_{1,t+1} \\ \Delta x_{2,t+1} &= .02 + u_{2,t+1} \end{aligned} \tag{16}$$

Table 18 reports simulations results. The estimators tend to converge to the true values but

n=250	MEAN	RMSE	MAE	Percentiles				
				5	25	50	75	95
$x_{1,t} - x_{2,t} > 0$								
$\mathrm{a}^+ - a_0^+$	0.037	0.190	0.150	-0.259	-0.085	0.027	0.159	0.367
$\mathrm{b}^+ - b_0^+$	0.010	0.171	0.171	-0.264	-0.108	0.006	0.123	0.287
$\mathrm{d}^+ - d_0^+$	0.002	0.127	0.101	-0.210	-0.083	-0.001	0.091	0.211
$x_{1,t} - x_{2,t} \leq 0$								
$a^- - a_0^-$	-0.024	0.172	0.134	-0.316	-0.130	-0.014	0.089	0.244
$b^- - b_0^-$	-0.009	0.134	0.105	-0.228	-0.099	-0.012	0.077	0.206
$d^- - d_0^-$	0.002	0.097	0.077	-0.163	-0.062	0.003	0.065	0.164

Table 18: **Distribution of estimators** - The estimators are obtained by setting the cointegrating coefficient at -1.

their distributions are quite dispersed.

9.2 Stability analysis

To ascertain that estimation results are not specific of the considered samples, recursive estimation of the coefficients is performed. Estimates are found to be stable over time. The estimated loadings in regime 1 and regime 2 for the UK and GE pair are reported in Figure 2.[10]

9.3 Heteroskedasticity analysis

A visual inspection of Figure 3 suggests that data series are characterized by volatility varying over time. It is interesting to analyse whether different levels of volatility are associated with different regimes. If so by estimating separately the variances for each regime, ARCH effects should decrease[11]. Consider the TVECM in (4) and let e_1 and e_2 be the estimated residuals

[10]The remaining cases are not reported for the sake of space and are available upon request.

[11]This does not affects coefficients estimates since a ML estimates under assumption that resides are i.i.d. have been performed

	UK-FR	GE-NE	GE-FR	UK-NE	NE-FR	UK-GE
$ARCH(5)$-E	-*	*-	**	**	**	-*
$ARCH(5)$-E1	-*	**	–	–	–	-*
$ARCH(5)$-E2	–	–	–	-*	-*	–

Table 19: **Heteroscedasticity**

corresponding to the two regimes.

Table 19 summarizes the results. In all cases, resides of linear VECM exhibit ARCH(5) effects in at least one equation. For the GE-FR pair ARCH(5) effects disappear by splitting the regimes. For the remaining pairs, evidence of autoregressive heteroscedasticity is found in the ”standard” state (regime 1 in case of GE-NE and UK-GE, and regime 2 for UK-NE and NE-FR). These findings suggest two considerations: i) ARCH effects may disappear from the ’extreme’ regime because a few observations are found in this regime; ii) observations that follow in regime 2 are concentrated in a short time frame (see Figure 6).

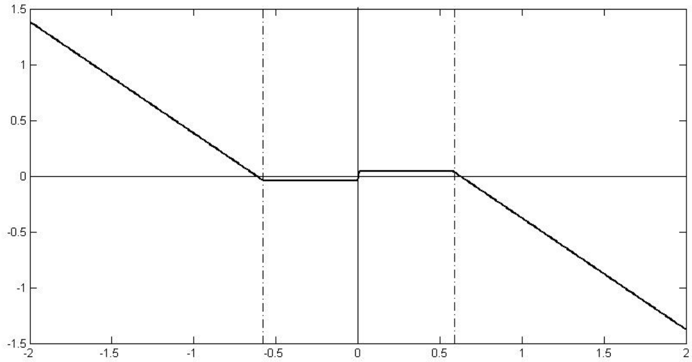
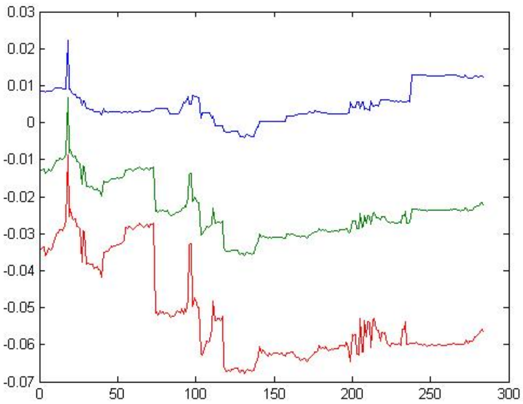
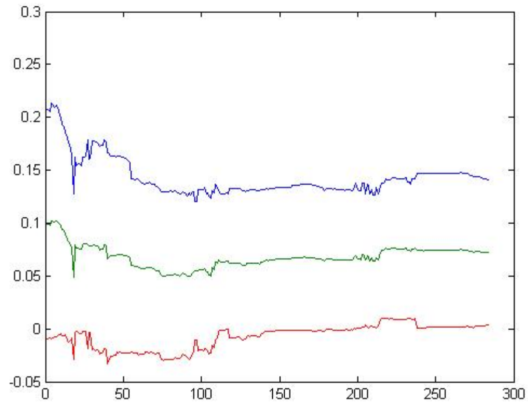


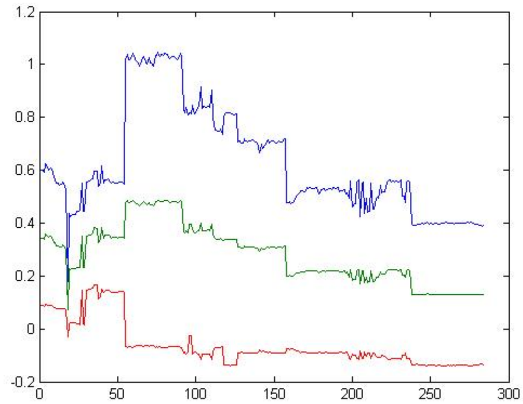
Figure 1: Δz_{t+1} on z_t with $(a^+, b^+, d^+; a^-, b^-, d^-) = (.02, .6, -.02; -.02, -.6, .02)$



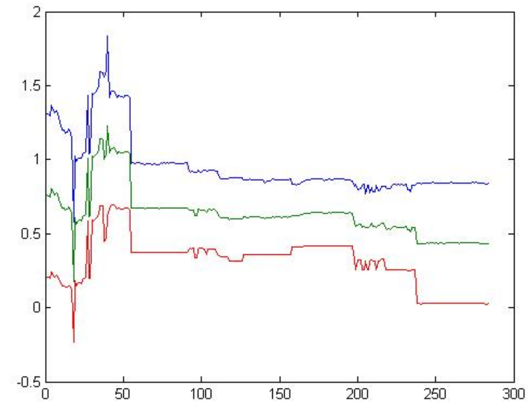
(a) Equation1 Regime1



(b) Equation2 Regime1

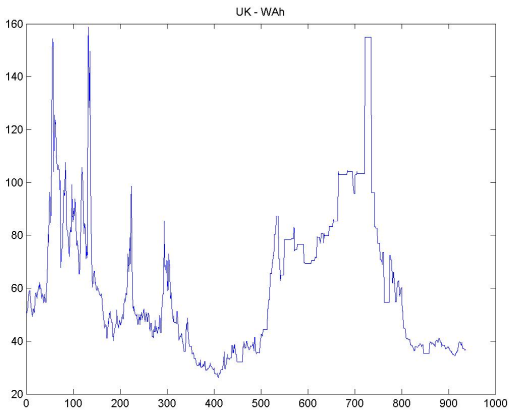


(c) Equation1 Regime2

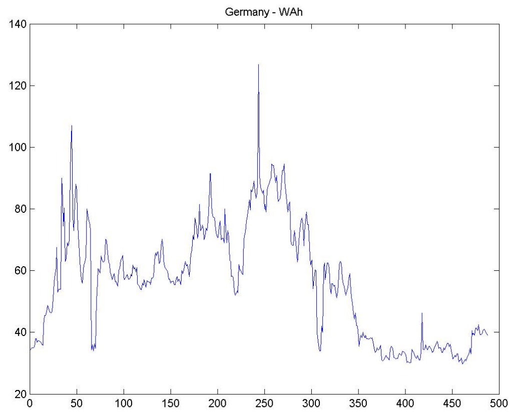


(d) Equation2 Regime2

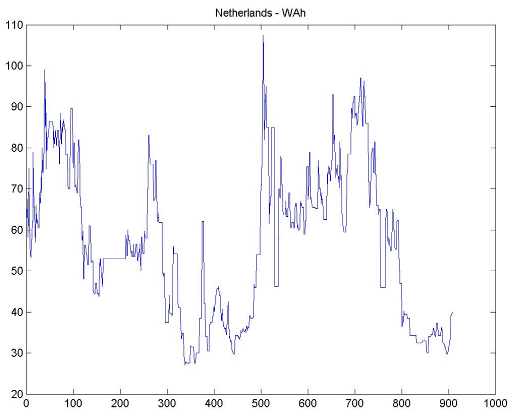
Figure 2: Recursive coefficients estimates - UK-GE pair



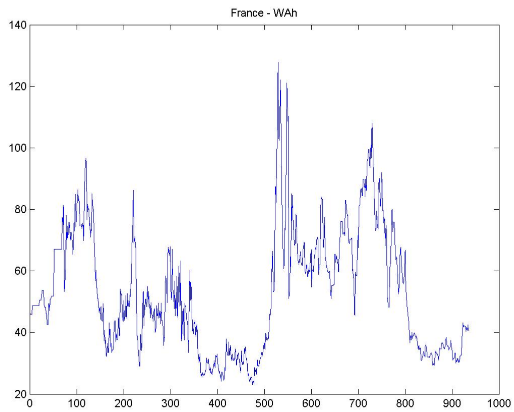
(a) United Kingdom



(b) Germany

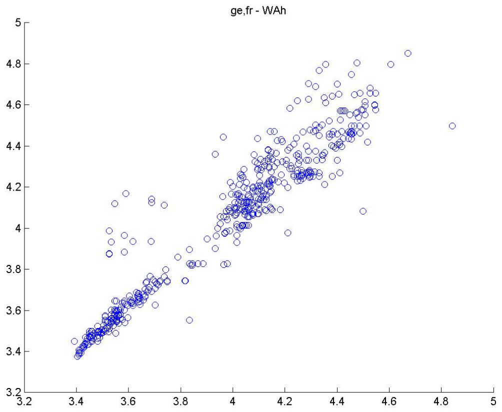


(c) Netherlands

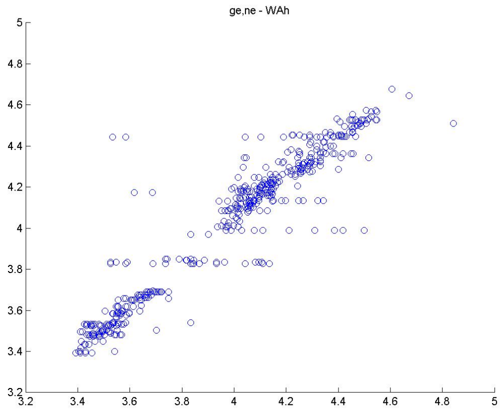


(d) France

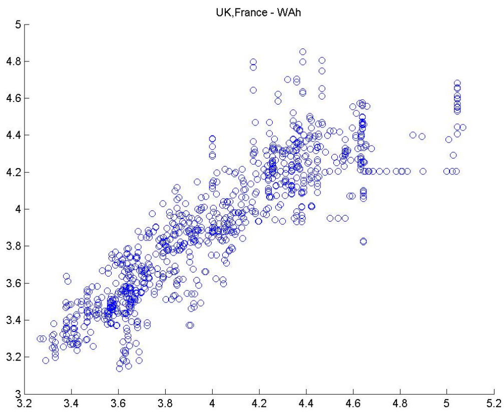
Figure 3: Week ahead baseload electricity prices



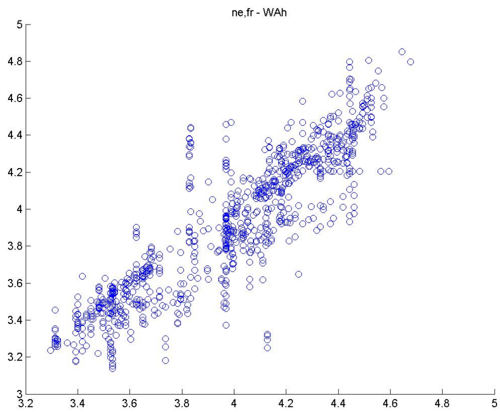
(a) Germany - France, 2007.9 - 2009.9



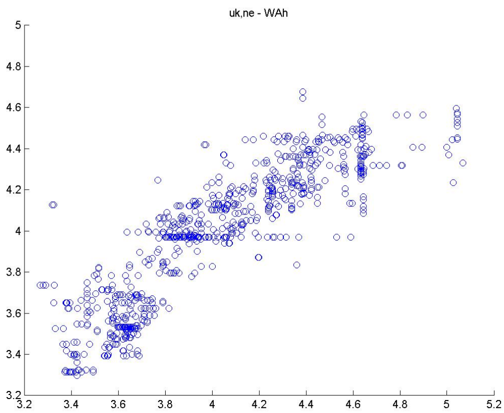
(b) Germany - Netherlands, 2007.9 - 2009.9



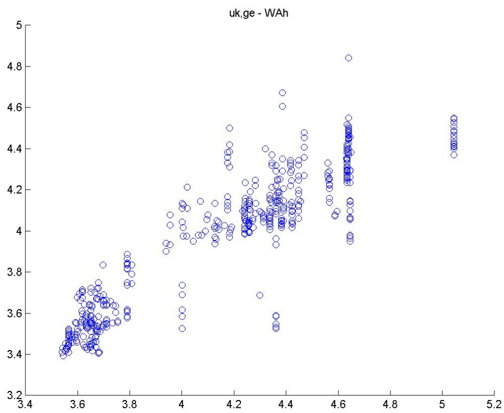
(c) United Kingdom - France, 2005.6 - 2009.9



(d) Netherlands - France, 2005.6 - 2009.9

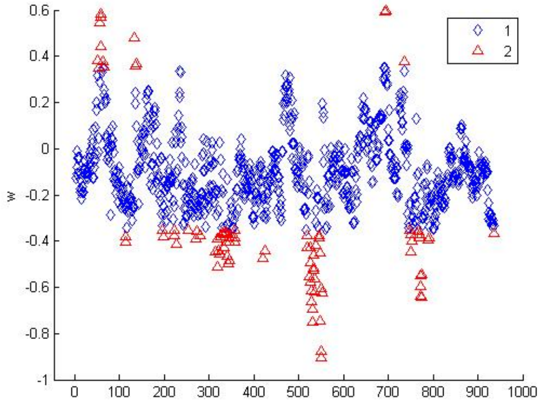


(e) United Kingdom - Netherlands, 2005.6 - 2009.9

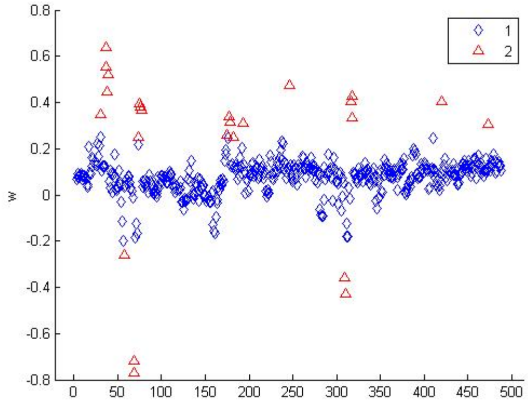


(f) United Kingdom - Germany, 2007.9 - 2009.9

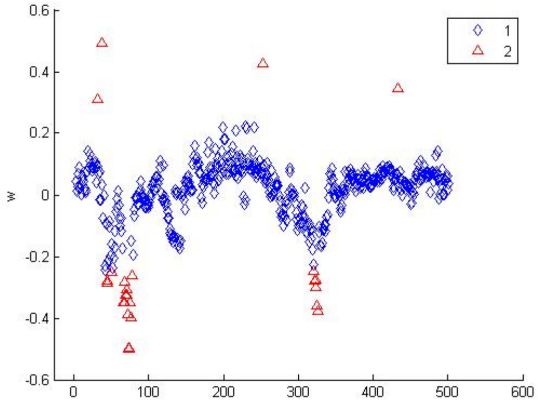
Figure 4: Scatter Plots of series



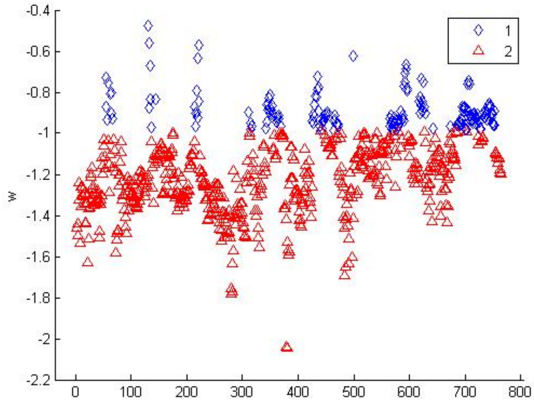
(a) eq United Kingdom - France



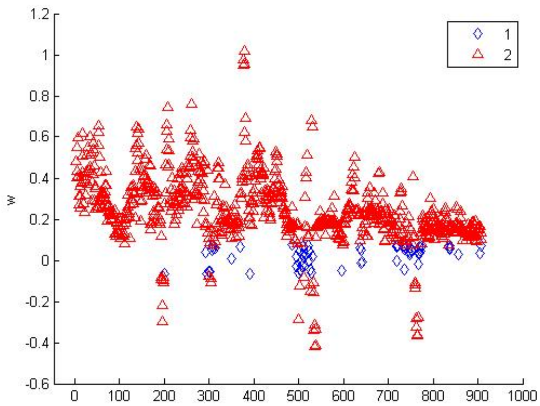
(b) eq Germany - Netherlands



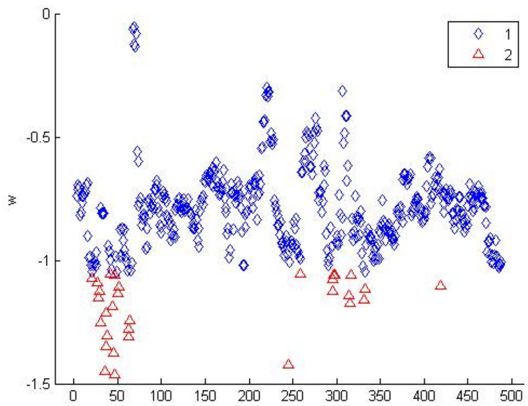
(c) eq Germany - France



(d) eq UK - Netherlands



(e) eq Netherlands - France



(f) eq UK - Germany

Figure 5: Equilibrium term by regime

Part III

The Health Effects of Climate Change: a Survey of Recent Quantitative Research

joint with Matteo Manera, Aline Chiabai and Anil Markandya.[1]

Abstract

In recent years there has been a large scientific and public debate on climate change and its direct as well as indirect effects on human health. According to World Health Organization (WHO, 2006), some 2.5 million people die every year from non-infectious diseases directly attributable to environmental factors such as air pollution, stressful conditions in the workplace, exposure to chemicals and to environmental factors. Changes in climatic conditions and climate variability can also affect human health via changes in biological and ecological processes that influence the transmission of several infectious diseases (WHO, 2003). In the past fifteen years a large amount of research on the effects of climate changes on human health has addressed two fundamental questions (WHO, 2003). First, can historical data be of some help in revealing how short-run or long-run climate variations affect the occurrence of infectious diseases? Second, is it possible to build more accurate statistical models which are capable of predicting the future effects of different climate conditions on the transmissibility of particularly dangerous infectious diseases? The primary goal of this paper is to review the most relevant contributions which have directly tackled those questions, both with respect to the effects of climate changes on the diffusion of non-infectious and infectious diseases. Specific

[1]In particular, Section 3 has been entirely written by myself and it has been the object of minor revisions by my coauthors; Section 2 has been developed jointly by myself and Matteo Manera; the Introduction and the Conclusion of the paper have been redacted by myself and completed by the other authors.

attention will be drawn on the methodological aspects of each study, which will be classified according to the type of statistical model considered. Additional aspects such as characteristics of the dependent and independent variables, number and type of countries investigated, data frequency, temporal period and robustness of the empirical findings are examined.

1. Introduction. Some facts and opinions on the relationship between climate change and health

In recent years there has been a large scientific and public debate on climate change and its direct as well as indirect effects on human health.

According to World Health Organization (WHO, 2006), some 2.5 million people die every year from non-infectious diseases directly attributable to environmental factors such as air pollution, extreme weather events, stressful conditions in the workplace, exposure to chemicals such as lead, and exposure to environmental tobacco smoke.

In particular, lead exposure has been estimated to account for 2% of the ischaemic heart disease burden and 3% of the cerebrovascular disease burden (WHO, 2003). Exposure to outdoor air pollution accounted for approximately 2% of the global cardiopulmonary disease burden (WHO, 2003). In the US, about 12% of the ischaemic heart disease burden has been related to occupation, for the age group 20-69 years. This estimate has been based on the specific risk factors of job control, noise, shift work and environmental tobacco smoke at work (Steenland et al., 2003). In Finland, it has been estimated that occupational risks account for 17% of the deaths from ischaemic heart disease, and 11% of those from stroke (Nurminen and Karjalainen, 2001). In Denmark, the occurrence of cardiovascular diseases is related to the type of occupation. Specifically, a reduction of 16% (22%) in the cardiovascular disease burden can be attributable to men (women) with non-sedentary occupations (Olsen and Kristensen, 1991).Changes in climatic conditions and climate variability represent a further factor which can affect human health directly or indirectly via changes in biological and ecological processes that influence the transmission of several infectious diseases (WHO, 2003). Direct effects on human health include, for example, thermal stresses due to increased frequency and intensity heat waves (cardiovascular and respiratory diseases, heat exhaustion), and deaths and injuries due to extreme weather events. Indirect effects include malnutrition, food-, water- and vector-borne diseases, together with increased morbidity due to the combined effect of exposure to high temperature and air pollution.

Empirical evidence suggests that malaria varies seasonally in highly endemic areas and is probably the vector-borne disease more sensitive to long-run climate changes. For example, the comparison of monthly climate and malaria data in highland Kakamega, Western Kenya, highlights a close association between malaria transmission and monthly maximum temperature anomalies over the years 1997-2000 (Githeko and Ndegwa, 2001). The effects of soil moisture to determine the causal links between weather and malaria transmission has been studied by Patz et al. (1998). For the most common mosquito species *Anopheles gambiae*, the soil moisture predicts up to 45% and 56% of the variability of human biting rate and entomological inoculation rate, respectively. The link between malaria and extreme climatic events has long been the subject of study on the Indian subcontinent as well as in various other countries. Early in the twentieth century, the Punjab region experienced periodic epidemics of malaria. Excessive monsoon rainfall and the resultant high humidity were clearly identified as major factors in the occurrence of malaria epidemics. More recently, time-series analyses have shown that the risk of a malaria epidemic increased approximately five-fold during the year following an El Niño year in Indian region (Bouma and van der Kaay, 1994). Furthermore, a strong correlation is found between both annual rainfall and the number of rainy days and the incidence of malaria in most districts of Rajasthan and in some districts in Gujarat (Akhtar and McMichael, 1996). The relationship between reported malaria cases and El Niño has been documented for Venezuela, where, during the whole twentieth century, malaria rates increased on average by over one-third in the year immediately following an El Niño year (Bouma and Dye, 1997).

However, it is widely acknowledged that climate changes are only one of many important factors influencing the incidence of infectious diseases and that their effects are very unlikely to be independent of socio-demographic factors (e.g. human migrations, transportation, nutrition), or of environmental influences (e.g. deforestation, agricultural development, water projects, urbanization). In particular, it has been estimated that about 42% of the global malaria burden, or half a million deaths annually, could be prevented by environmental management, although this proportion varies significantly across different regions: it is 36% in the Eastern Mediterranean Region; 40% in the Western Pacific Region; 42% in sub-Saharan Africa; 42% in the South-East Asia Region; 50% in the European Region; 64% in the Region of the Americas (WHO, 2006).

Nevertheless, in the past fifteen years a large amount of research on the effects of climate changes on human health has addressed two fundamental questions (WHO, 2003). First, can historical data be of some help in revealing how short-run or long-run climate variations affect the occurrence of infectious diseases? Second, is it possible to build more accurate statistical models which are capable to predict the future effects of different climate conditions on the transmissibility of particularly dangerous infectious diseases?

The primary goal of this work is to review the most relevant contributions which have directly tackled those questions, with respect to the effects of climate changes on the diffusion of non-infectious and infectious diseases. Specific attention will be drawn on the methodological aspects of each study, which will be classified according to the specific problem in question, as well as the type of statistical model considered.[1]

As far as the specific problem addressed by each study is concerned, we refer to:

- **Primary studies**, which analyze the direct effects of rising temperatures on the burden of diseases;
- **Secondary studies**, which consider socio-economic effects of temperatures growth including Integrated Assessment Models (IAMs), General Equilibrium Models (GEMs) and Global Trade Analysis Project Models (GTAP);
- **Comparative Risk Assessments** (CRA), which integrate climate models for projecting future climate changes and "primary studies" for estimating the effects on health.

[1] Additional aspects such as characteristics of the dependent and independent variables, number and type of countries investigated, data frequency, temporal period spanned by the analysis, and robustness of the empirical findings are examined.

In terms of the type of statistical model which each of the surveyed study is based on, the following broad classes emerge:

- **Stationary and non-stationary time series models**, such as ARMAX (Auto Regressive Moving Average with exogenous variables) models, ECM (Error Correction Models), possibly with seasonal components;

- **Non-parametric forecasting models**, such as single and double exponential smoothing, Holt-Winters methods (additive, no seasonal, multiplicative);

- **Panel data and spatial models,** such as fixed and random effects models, dynamic panel data models, spatial lag and spatial error models.

The paper is organized as follows. Section 2 presents a taxonomy of the most popular classes of statistical models used to analyze the relationship between climate variations and the diffusion of non-infectious and infectious diseases. In Section 3 a significant number of quantitative contributions are discussed in detail, with particular emphasis on the specific problem addressed, as well as the type of statistical model adopted. Section 4 contains some conclusions.

2. Statistical models for the relationship between climate change and health: a taxonomy

Statistical models are important tools for analysing the complex relationship between climate changes and human health, since they allow researchers to link crucial climate variables (such as temperature and precipitations) at global or regional levels to the occurrence of the disease under scrutiny (WHO, 2003).

In this section, we briefly describe the basic specification for each class of models. We start with univariate models for stationary and non-stationary time series, such as ARMAX with exogenous variables, and ECM. The concepts of deterministic and stochastic trends are revisited, as well as the implications of cointegration and seasonality. We then present the most popular single-equation exponential smoothing methods for predicting the future values of a time-series. Finally, we consider the basic models for static and dynamic panel data, as well as for spatial statistics.

2.1. Models for stationary and non-stationary time series

In applied statistics, the standard model that takes into account the random nature and time correlations of the variable under study (e.g. the occurrence of a particular disease), Y_t, t=1,…,T, is the Auto Regressive Moving Average (ARMA) model (see, among others, Lütkepohl and Krätzig, 2004). It is composed of two parts: the autoregressive component and the moving average component. The autoregressive (AR) model of order p, AR(p), can be written as:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + ... + \alpha_{t-p} Y_{t-p} + \varepsilon_t \qquad (1)$$

where α_0 is a constant and ε_t, t=p+1, …, T, are the error terms, generally assumed to be independent and identically-distributed normal random variables, with E(ε_t)=0 and Var(ε_t)=σ^2, for any t (i.e. white noise errors). The parameters $\alpha_1, \alpha_2, ..., \alpha_p$ are referred to as the AR coefficients.

The moving average (MA) models can be interpreted as the representation of a time series which is generated by passing a white noise process through a non recursive linear filter. The notation MA(q) refers to the moving average model of order q:

$$Y_t = \theta_0 + \varepsilon_t + \theta_1 \varepsilon_{t-1} + ... + \theta_q \varepsilon_{t-q} \tag{2}$$

A linear model for Y_t based on both past values (1) and innovation values (2) is known as an Auto Regressive Moving Average (ARMA). The notation ARMA(p,q) refers to p autoregressive terms and q moving average terms:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{3a}$$

or

$$\alpha(L) Y_t = \alpha_0 + \theta(L) \varepsilon_t \tag{3b}$$

where $\alpha(L)$ and $\theta(L)$ are polynomials in the lag operator L of order p and q, respectively.

In order to describe the relationship between the occurrence of a specific disease and climatic variables more accurately, an Auto Regressive Moving Average model with eXogenous variables (ARMAX) can be used. The notation ARMAX(p,q,b) refers to a model with p autoregressive terms, q moving average terms and b exogenous variables. This model nests the AR(p) and MA(q) models, and linear combinations of b explanatory variables, $X_{r,t-sr}$, r=1,…,b, sr=0,…,wr. An ARMA(p,q,b) model can be written as:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{s1=0}^{w1} \delta_{1,s1} X_{1,t-s1} + \ldots + \sum_{sb=0}^{wb} \delta_{b,sb} X_{b,t-sb} + \varepsilon_t \qquad (4)$$

A number of variations of ARMA models are commonly used in statistics, according to whether the series Y_t and $X_{r,t}$ are integrated or exhibit seasonalities. We explain the concept of integration below.

It is well known that classical statistical inference is based on the concept of stationarity. A time series Y_t, t=1,...,T, is said to be (weakly) stationary if E(Y_t) and Var(Y_t) are constant for any t and finite, and Cov(Y_t, Y_{t-k})=Cov(Y_s, Y_{s-k}), for t different from s (what matters is only k, not the time location). At the same time, it is widely acknowledged that most economic, social-demographic, environmental and climatic time series are non-stationary, since they contain trends (deterministic and/or stochastic).

The simplest example of a non-stationary time series with a stochastic trend is the Random Walk (RW), i.e. the AR(p) model (1) with p=1 and α_1=1. If Y_t follows a RW, then Y_t is said to be integrated of order 1, or I(1), since we have to apply the difference operator Δ once to Y_t ($\Delta Y_t = Y_t - Y_{t-1}$) in order to obtain a transformed series which is integrated of order 0, or I(0), i.e. a stationary time series. In general, a time series Y_t is I(d) if we have to apply d times the difference operator to make it stationary, i.e. $\Delta^d Y_t$ is I(0). In general, the order of integration d of most economic, social-demographic, environmental and climatic variables is taken to be an integer equal to 0, 1 or 2.

The classical distributions which are at the basis of many statistical tests (i.e. t, F, chi-square, etc.) are no longer valid if the series are I(d), d = 1, 2. At this stage, two questions arise. First, is it possible to test for the order of integration d of a time series? Second, is it possible to use statistical inference with integrated series?

The answer to the first question is given by the tests for the order of integration of a time series (also known as unit-root tests), the most popular of which is the Augmented Dickey-Fuller (ADF) t-test on the null hypothesis $\rho = 0$ (i.e. d is at least equal to 1) against the alternative hypothesis $\rho < 0$ (i.e. $d = 0$) in the regression model:

$$\Delta Y_t = \rho Y_{t-1} + \Sigma_i \pi_i \Delta Y_{t-i} + v_t \tag{5}$$

$t = 1,\ldots,T$ and $i = 1,\ldots,p$. The ADF test follows a special distribution, known as Dickey-Fuller distribution. The ADF test can be iterated to test any order of integration (on $\Delta^d y_t$), if d is an integer.

The answer to the second question is positive, provided the variables are cointegrated. If Y_t is I(1) and X_t is I(1), Y_t and X_t are said to be cointegrated if a linear combination $c_Y Y_t + c_X X_t$ is stationary, i.e. I(0) for given values of c_Y and c_X. Thus there is an equilibrium relationship.

A simple test for cointegration applies ADF to the residuals ε_t of the regression of Y_t on X_t, that is $Y_t = c_X X_t + \varepsilon_t$. Since the residuals are defined as the linear combination between Y_t and X_t with weights c_Y=1 and c_X given by the OLS coefficient of X_t, if the residuals are I(0) then Y_t and X_t are cointegrated.

The relationship between two variables Y_t and X_t, both I(1) and cointegrated, can be represented via an Error Correction Model (ECM), with possible asymmetric terms:

$$\Delta Y_t = \delta + \sum_{i=0}^{s} \alpha_i^+ \Delta X_{t-i}^+ + \sum_{j=0}^{q} \alpha_j^- \Delta X_{t-j}^- + \lambda^+ ECT_{t-1}^+ + \lambda^- ECT_{t-1}^- + u_t \tag{6}$$

where ΔX_t = X_t-X_{t-1}; ΔX^+ = ΔX if $\Delta X \geq 0$ and $\Delta X^+=0$ otherwise; $\Delta X^-=\Delta X$ if $\Delta X<0$ and $\Delta X^-=0$ otherwise; ECT_t are the residuals from the cointegrating regression of Y_t on X_t; $ECT^+=ECT$ if $ECT \geq 0$ and $ECT^+=0$ otherwise; $ECT^-=ECT$ if $ECT<0$ and $ECT^-=0$ otherwise. Parameters α^+ and α^- are the short-run marginal effects, while parameters λ^+ and λ^- are the speeds of adjustment of Y_t from t-1 to t to the equilibrium, once a disequilibrium has occurred in t-1.

Many economic, socio-demographic, environmental and climatic variables exhibit seasonal behaviour. As in the case of trends, the time series literature distinguishes between deterministic and stochastic seasonality. A non-stationary time series Y_t, observed at S equally spaced time intervals per year, is said to be seasonally integrated of order d, or SI(d), if $\Delta_S{}^d Y_t$ is a stationary and invertible ARMA process of the type described by equations (3) (Ghysels et al., 2003). The simplest seasonal model for non-stationary variables is the seasonal random walk (SRW): $Y_t = Y_{t-S}+\varepsilon_t$. The SRW model can be generalized to the seasonal integrated ARMA (SARIMA) model:

$$\alpha(L)\Delta_S^d Y_t = \theta(L)\varepsilon_t \tag{7}$$

where the polynomials $\alpha(L)$ and $\theta(L)$ in the lag operator L have all roots outside the unit circle, i.e., the AR part of equation (7) is stationary, while the MA part of equation (7) is invertible. An alternative way to model seasonality is via seasonal dummy variables, according to the following basic specification:

$$Y_t = \sum_{s=1}^{S} \gamma_s D_{st} + \varepsilon_t \tag{8}$$

where D_{st} is the seasonal dummy variable which takes the value of 1 when t falls in season s. The interpretation of this approach is that seasonality is essentially a deterministic phenomenon, so that the time series of interest is stationary around seasonally varying means. In empirical applications, equation (8) is typically combined with specifications (4) and (6) in order to build up more general and flexible models, which can also be used to produce out-of-sample forecasts of Y_t.

2.2. Non-parametric forecasting models

Exponential smoothing is a method of adaptive forecasting, which is useful in cases where the number of observations on which to base the forecasts is limited. The basic idea underlying exponential smoothing is that forecasts adjust on the basis of past forecast errors (Mills, 2003). If Y_t, t=1,...,T, is the time series to be forecasted and Y_t^* is the smoothed series, Y_t^* is calculated according to the following recursive model:

$$Y_t^* = \alpha Y_t + (1-\alpha)\mathrm{Y}_{t-1}^* \tag{9}$$

where $0<\alpha\leq 1$ is the smoothing factor. The smaller is α, the smoother is Y_t. Model (9) is referred to as single smoothing, and is appropriate for stationary, non-seasonal time series. By repeated substitutions in (9), Y_t^* can be written as a weighted average of past values of Y_t, where the weights

$(1\text{-}\alpha)^t$ decline exponentially with time. The out-of-sample forecasts from single smoothing are constant for all observations and are given by: $Y_{T+h}^{*} = Y_T$, for all $h>0$.

The method known as double smoothing applies single smoothing twice and is appropriate for time series which are non-stationary for the presence of a linear deterministic trend. The model is given by the following two recursive equations:

$$
\begin{aligned}
Y_t^{*} &= \alpha Y_t + (1\text{-}\alpha) Y_{t-1}^{*} \\
Y_t^{**} &= \alpha Y_t^{*} + (1\text{-}\alpha) Y_t^{**}
\end{aligned}
\tag{10}
$$

where Y_t^{**} is the double smoothed series. Forecasts from double smoothing are calculated as:

$$
Y_{T+h}^{**} = 2Y_T^{*} \text{-} Y_T^{**} + \alpha(Y_T^{*} \text{-} Y_T^{**})h/(1\text{-}\alpha) \tag{11}
$$

Equation (11) suggests that Y_{T+h}^{**} lies on a linear trend with intercept $2Y_T^{*}\text{-}Y_T^{**}$ and slope $\alpha(Y_T^{*}\text{-}Y_T^{**})/(1\text{-}\alpha)$.

A method which is suitable for a time series with a linear trend and additive seasonal variations is the so-called additive Holt-Winters. The smoothed series is given by:

$$
Y_{t+h}^{*} = a + bh + c_{t+h} \tag{12}
$$

where a and b are the permanent component and trend parameters, while c_{T+h} represent the additive seasonal factors. The coefficients are specified according to the following expressions:

$$a(t) = \alpha(Y_t\text{-}c_t(t\text{-}s))+(1\text{-}\alpha)(a(t\text{-}1)+b(t\text{-}1))$$

$$b(t) = \beta(a(t)\text{-}a(t\text{-}1))+1\text{-}\beta b(t\text{-}1) \tag{13}$$

$$c_t(t) = \gamma(Y_t\text{-}a(t+1))\text{-}\gamma c_t(t\text{-}s)$$

where α, β and γ are the smoothing parameters and s is the seasonal frequency. Forecasts are computed as:

$$Y_{T+h}^{*} = a(T) + b(T)h + c_{T+h\text{-}s} \tag{14}$$

If Y_t is a time series characterized by the presence of a linear trend and multiplicative seasonal variability, the multiplicative Holt-Winters model is typically applied. In this case, the smoothed series is given by the following modified version of (12):

$$Y_{t+h}^{*} = (a + bh)c_{t+h} \tag{15}$$

the evolution of the coefficients a, b and c_t being given by slightly modified versions of equations (13).

2.3. Panel data and spatial models

Many economic, socio-demographic, environmental and climatic variables are observed through time (t=1,...,T) and across "individuals" (i=1,...,N), where the notion of "individual" used in the present context is broad enough to embrace real individuals, households, countries, geographical areas, firms, economic sectors, etc. A variable observed through time and across individuals, Y_{it}, is said to have a panel data structure (Baltagi, 2001).

Modern econometrics and statistics distinguish between two broad classes of static models for panel data, fixed effect and random effects models. Although both approaches share the same idea of taking into account one major feature of panel data, namely individual heterogeneity, they provide radically different ways of modelling individual variability. The fixed effects model assumes that individual heterogeneity can be represented via individual-specific constants, as:

$$Y_{it} = \alpha_i + \sum_{r=2}^{K} \beta_r X_{rit} + u_{it} \tag{16}$$

where u_{it} is a classical error term. This model is appropriate if individual heterogeneity is systematically distributed among individuals, i.e. the sample of data is non-random. Since individual heterogeneity is represented by the additional regressors α_i, correlation between explanatory variables X_{it} and individual heterogeneity is allowed for in the fixed effects model. On the contrary, the random effects model assumes that individual heterogeneity is randomly distributed among individuals, hence it has to be represented as a classical random normal variable μ_i, which contributes to a composite error term, v_{it}:

$$Y_{it} = \alpha + \sum_{r=2}^{K} \beta_r X_{rit} + v_{it} \ , \ v_{it} = \mu_i + u_{it} \qquad (17)$$

OLS is consistent for the parameters β_r, $r = 2,\ldots,K$, of model (16), while GLS is consistent for the parameters in model (17). Since individual heterogeneity is part of the model error term in equation (17), correlation between individual heterogeneity and the explanatory variables X_{it} would lead to inconsistent estimates.

In applied statistics the autocorrelated structure of many time series variables is widely acknowledged. The simplest way to allow for data autocorrelation is to extend model (17) to include the lagged dependent variable as an additional regressor (dynamic panel data models). Unfortunately, the lagged dependent variable is correlated with the composite error term v_{it}, leading to inconsistency of the LS estimators. This inconsistency is still present if the variables involved in model (17) are transformed in first differences, in order to eliminate the random effects μ_i:

$$\Delta Y_{it} = \gamma \Delta Y_{it-1} + \sum_{r=2}^{K} \beta_r X_{rit} + u_{it} \qquad (18)$$

Equation (18) is typically estimated with instrumental variables techniques (e.g. Anderson-Hsiao and Arellano-Bond estimators).

When sample data have a natural location component, two problems arise, namely spatial heterogeneity and spatial dependence (see Anselin, 1988; for an introduction to spatial econometric models see, among others, Cattaneo, 2008 and Cattaneo et al., 2010). Spatial heterogeneity (SH) refers to the fact that many phenomena lead to structural instability over space, in the form of different response functions or systematically varying parameters. SH induces familiar problems such as heteroskedastic random coefficient variation and switching regressions. Spatial dependence

(SD) occurs when sample data observations exhibit correlation with reference to points or location in space. Formally, one observation associated with a location i depends on other observations at locations j, $j \neq i$, that is $Y_i = f(Y_j)$, i=1,…, N; $j \neq i$. In general, the dependence is among several observations, as the index i can take on any value from i=1,...,N.

Two reasons are commonly given to explain SD. First, data collection of observations associated with spatial units might reflect measurement errors. Second, the spatial dimension of socio-demographic, economic or regional activities (e.g. environment and climatic variables) may be an important aspect of a modelling problem.

In spatial data analysis the spatial structure of the observations is made explicit by means of spatial weight matrices. The elements of the weight matrix are non-stochastic and exogenous to the model and derived from alternative criteria, such as contiguity (neighbouring units should exhibit a higher degree of spatial dependence than units located far apart), Cartesian space (physical distance matters), non-geographic factors (economic/social proximity).

The presence of spatial correlation between the units of observations can be detected by means of tests which capture the extent to which values similarity matches with locations similarity. In this context, positive spatial correlation exists if likewise values tend to cluster in space; negative correlation exists if the locations are surrounded by neighbour with dissimilar values; zero spatial correlation implies that it is not possible to identify a specific spatial pattern of values. This situation is also described as spatial randomness, as values observed at a location do not depend on values observed at neighbouring locations.

A fairly general spatial econometric model contains both a spatial lagged dependent variable and a spatially autocorrelated error term, and can be written, using matrix notation, as:

$$\begin{aligned} Y &= \rho W_1 Y + X\beta + U \\ U &= \lambda W_2 U + E \end{aligned} \tag{19}$$

$$E \sim N(0, \sigma^2 I_N)$$

However, model (19) is rarely used in practice, because there are problems of identification whenever W_1 equals W_2. If W_2=0 in specification (19), the so-called spatial lag (SL) model is obtained, whereas the spatial error (SE) model originates when W_1=0 in (19). The SL model is appropriate when the focus of interest is the assessment of the existence and strength of spatial interactions, whose existence is directly derived from an economic model. SD in the SE model is referred to nuisance dependence. This model is appropriate when the concern is with correcting for the potentially biasing influence of the spatial autocorrelation, due to the use of spatial data, irrespective of whether the model is spatial or not.

The reduced form of the SL model is:

$$Y = (I_N - \rho W_1)^{-1} X\beta + (I_N - \rho W_1)^{-1} E \tag{20}$$

where $\left(I_N - \rho W_1\right)^{-1}$ is a full matrix, which induces error terms in all locations. The estimation method of the SL model is 2SLS or ML. The spatial lag term $W_1 Y$ in equation (19) yields a measure of spatial dependence that controls for the effect of the included exogenous variables. It indicates the effects of spatial autocorrelation after controlling for other variables. On the contrary, OLS is unbiased for the SE specification, although it is an inefficient estimator, since it ignores the specific variance structure for the errors.

3. Modelling the relationship between climate change and health. What does the literature say?

3.1. Quantitative studies

3.1.1. Primary studies

Time series models have been used extensively for predicting the evolution pattern of diseases, and more specifically to assess the relationship between environmental exposure and mortality or morbidity over long time periods. These predictions are a necessary step for quantifying potential impact of climate on health and the related costs. In the field of climate based Early Warning Systems (EWS), which are used to predict the occurrence of epidemics of infectious diseases, Chaves and Pascual (2007) review and compare linear and non-linear models for forecasting seasonal time series of diseases. Using American cutaneous leishmaniasis, as an example, the models are evaluated based on the predictive R2 for forecasting the data “out-of-fit”. Seasonal autoregressive models that incorporate climatic covariates are found to provide the best forecasting performance. Additionally, a bootstrapping experiment shows that the relationship of the disease time series with the climatic covariates is strong and consistent for the seasonal autoregressive (SAR) modeling approach. While the autoregressive part of the model is not significant, the exogenous forcing due to climate is always statistically significant. Prediction accuracy can vary from 50% to over 80% for diseases burdens at time scales of one year or shorter.

A different strategy for predicting the pattern of diseases is given by Medina et al. (2007), who investigate the dynamics of diarrhea, acute respiratory infection (ARI), and malaria in Niono, Mali. The authors observe that these disease time-series often *i)* suffer from non-stationarity; *ii)* exhibit large inter-annual plus seasonal fluctuations; and, *iii)* require disease-specific tailoring of forecasting methods. To accommodate these characteristics they suggest using a non-parametric technique, the multiplicative Holt-Winters method (MHW). This is a recursive method that can be described as follows: *i)* based on past information and pseudo-parameters initialization the MHW produces point forecasts (the method also decompose the time series into level, trend (rate of change), seasonal, and approximately serially uncorrelated residual TS components); *ii)* point forecasts are recursively revised through residuals bootstrap to produce median forecasts and their 95% confidence interval bounds; *iii)* these median forecasts and contemporaneous time-series information is used by the MHW program to update the forecasts and prediction interval bounds. Step *i)* also decompose the time series (TS) into level, trend (rate of change), seasonal, and approximately serially uncorrelated residual TS components.

Using longitudinal data from 01/1996 to 06/2004 the authors find that the MHW produces reasonably accurate median 2- and 3-month horizon forecasts for the considered non-stationary time-series, i.e., 92% of the 24 time-series forecasts generated (2 forecast horizons, 3 diseases, and 4 age categories = 24 time-series forecasts) have mean absolute percentage errors about 25%. In their experiments the MAPE is smaller for the forecasts of monthly consultation rates for malaria and ARI, while the accuracy decreases for diarrhea's consultation rates.

Other time series approaches have been used to explore the issue of extreme climatic events' impacts. Curriero et al. (2002) perform time series analyses to estimate the temperature-mortality association for eleven eastern US cities from 1973 to 1994. By using log-linear models for time series data the authors find the following evidences: *i)* current and recent days' temperature are the weather factor most strongly predictive of mortality; *ii)* it appears to exist a threshold temperature below which mortality tends to decrease as temperatures increases form the coldest days, and above which mortality risk increases as temperature increases; *iii)* a strong association exists between mortality associated to extreme temperatures and latitude.

Shakoor et al. (2006) use time-series models to analyze mortality due to thermal stresses during heat waves compared to total mortality occurring throughout the whole summer, to understand what fraction of the total impact is attributable to temperature extremes. In the same context, Keatinge et al. (2000) estimate the heat-related mortality due to climate change in Europe, using time-series data and taking into account the threshold temperature where mortality is lowest. The findings suggest that European population have adapted to average summer temperatures, and might adapt to future higher temperatures with only a minor increase in heat-related deaths. These studies suggest that the process of acclimatization should be taken into account when assessing the impact of heat waves and increased temperatures.

Finally we mention Rodó et al. (2002) who present a time-series analysis of the relationship between El Niño/Southern Oscillation (ENSO) and the prevalence of cholera in Bangladesh using mortality data recorded on a monthly period from 1893 to 1940. Singular spectrum analysis (SSA) is used to capture discontinuous dynamics and trends. The technique allows to decompose the irregular dynamics of the time series and to isolate the inter-annual variability of the data. Their findings suggest that ENSO is responsible for more than 70% of the dynamics of the disease, this relationship being discontinuous in time.

3.1.2. Secondary studies

Cross-section and panel data models

A subject that is contiguous but relevant for the impact of climate on health and its ethical implications is the relationship between pollution and income. Rupasingha et al. (2004) use and extended spatial econometric analysis to investigate whether it exists an inverse-U relationship between various pollution indicators and county per capita GDP in the US (the so-called environmental Kuznets curve, EKC). The authors emphasize that the EKC is conditional on various structural features (e.g. technology, education, political practices) of each locality. Moreover, they expand the analysis including ethnic diversity among the covariates and by controlling for spatial dependence. Their initial results support the existence of the EKC relationship. The inclusion of spatial autocorrelation is found to raise the turning point of the curve. Another result is that more ethical diverse counties are more polluted. Finally, incorporating a cubic term for income, they find that the toxicity index eventually increases again as income continues to rise.

Salomon and Murray (2002) analyze the patterns of diseases and mortality rates in the framework of the literature on epidemiologic transition (Omran, 1971). The authors provide a cause-of-death analysis for WHO data on mortality by age and sex and recorded cause by 1950 to 2002, and use models for compositional data. Specific causes of death are modeled as a function of the overall level of mortality and the income per capita. The findings suggest that considerable variations in cause-of-death patterns across countries and over time are coupled with empirical regularities. Indeed, as mortality levels declines the composition of the causes changes. The effects of mortality declines are more noticeable for children and young adults (with a shift from Group 1 diseases - infectious and parasitic diseases, respiratory infections, maternal conditions, etc. - to Group 2 diseases - diabetes, endocrine disorders, etc. - and Group 3 - injuries - in proportions that vary according to age and sex). In older adults, the composition of mortality remains stable while deaths shift to older ages. Moreover, in many societies, "protracted and polarized" epidemiologic transitions reflect heterogeneity of the social strata.

General equilibrium models

General Equilibrium models have been used to estimate the welfare costs (or benefits) of health impacts of climate variables.

Martens (1998a) conducts first a meta-analysis of aggregated effects of a change in temperature on mortality for total, cardiovascular and respiratory mortality. Second, he combines these effects with projections of changes in baseline climate conditions of 20 cities, according to climate change scenarios of three General Circulation Models (GCMs). The author finds that for most of the cities included, global climate change is likely to lead to a reduction in mortality rates due to decreasing winter mortality. This effect is most pronounced for cardiovascular mortality in elderly people in cities which experience temperate or cold climates at present.

Similar to Martens (1998a), Tol (2002) consider GCM (General Circulation Models) based studies' results to estimate (and evaluate in monetary terms) the impacts of climate change for a wide range of market and non-market sectors (agriculture, forestry, water, energy, costal zones and ecosystems, as well as mortality due to vector-borne diseases, heat stress and cold stress). The author estimates that small increases in temperatures would bring some benefits (mainly for the developed world). The conclusion on the global impact of climate change depends crucially on the weights used to aggregate the regional values. Using the simple sum the benefits amount to 2% of GDP. Considering globally averaged prices to value non-markets goods the impact is a 3% reduction of global income. According to equity (ratio of global to regional per capita income) - weighted results the world impact is null. Global impacts become negative beyond 1°C increase in temperatures.

Bosello et al. (2006) make use of the General Equilibrium Model (GTAP) in an unconventional approach in order to analyse how health impacts would affect the general economy. Their aim is to estimate the indirect costs on the economic system derived from the health effects as a result of an increase of one degree Celsius in global mean temperature. They estimate the impact on labour productivity and health care expenditures for both the public system and private households, as well as the impacts on GDP. Six health outcomes are considered (cardiovascular disease, respiratory disease, diarrhoea, malaria, dengue and schistosomiasis). The impacts on health are taken from different studies (Tol, 2002; Martin and Lefebvre, 1995; Morita et al., 1994) that estimate the change in mortality due to an increase of one degree in the global mean temperature. Using data of GTAP model of Hertel and Tsigas (2002) and IMAGE team (2001) (see the paper and the references therein for a more accurate description) the authors find an increase in mortality and morbidity due to respiratory illness, malaria, dengue fever and diarrhoea, with increased costs of illness. In contrast, they evidence a decrease in cardiovascular diseases and schistosomiasis, which dominate the overall impact, leading to a negative trend in the additional expenditure for health care in all countries.

Although the results of Bosello et al. (2006) go on the same direction (but with stronger evidence) as the conclusions of earlier papers (e.g. Martens, 1998a; and Tol, 2002), they are controversial. Indeed, Ackerman and Stanton (2006) challenge Bosello et al. (2006), Martens (1998b) and Tol (2002). The authors argue that Bosello et al. (2006) results are biased due to the omission of extreme weather events and human adaptation to gradual temperatures changes. The main concern is about the use of average temperatures instead of increased variability in local temperatures, which results in an increase of the frequency of extreme hot or cold. Another important issue to be considered in this context is related to the population expected to support heat- and cold-related stresses. In Bosello et al. (2006), as well as in Tol (2002), heat stresses are assumed to impact the urban population only, while cold-related diseases are expected to occur in both the rural and urban population. This assumption might have a strong influence on final results and needs therefore to be further analyzed, especially when considering countries with large rural population (De Dube et al., 2005).

As seen above Bosello et al. (2006) and Ackerman and Stanton (2006) find contrasting evidence, which is partly related to whether or not extreme climatic events are considered. This suggests that what projected changes in temperatures are considered has a big impact on the results. A review of main findings of the economic literature on climate effects is given as a part of the research of Stern (2007). Also an advance in this field of research and modeling is given by the author (see next section for a review on the Stern Report).

3.1.3. Comparative risk analyses

Using comparative risks assessments (CRA), which integrate climate models and the evaluation of the health effects of rising temperatures, Ezzati et al. (2003) estimate the potential gains that would derive from combined preventive measures. The authors provide an estimation of the joint effects of 20 selected leading risk factors in 14 epidemiological sub-regions (as a proxy of the world). Among the major risk factors they include environmental risks (such as unsafe water, sanitation and hygiene) that are correlated with the climate. As a tool for the estimation they define the potential impact factor (PIF) as the reduction in population diseases burden or mortality that would occur if the current exposures to multiple risk factors were reduced to an alternative exposures distribution (see the article for a formal definition of the PIF). They find that globally 47% of premature deaths and 39% of total disease burden in 2000 resulted from the joint effects of the considered risk factors. Their results suggest that joint actions would result in a massive reduction of death due to the burden of diseases. Moreover, they find evidence that reducing multiple major risk factors would decrease some of the differences between regions.

McMichael et al. (WHO, 2003) provide projections of relative risk attributable to climate change under alternative exposure scenarios, using global climate models and comparative risk assessment. The results are presented for broad WHO geographical regions, and include malaria, diarrhea, malnutrition and heat-related stresses. The study presents some limitations which should be investigated in future research in order to estimate the burden of disease. The issue of improved access to water and sanitation systems is not considered, nor is the level of economic development, although these are important factors influencing the population vulnerability. A second limitation is that the correlation between different health outcomes is not evaluated. This is particularly important for malnutrition which is strictly related to occurrence of other diseases. Finally, the model for malaria relates climate variables to geographical areas at risk (and population), instead of disease incidence, and estimates the impacts related to changes in the average temperature while not accounting for climate variability.

In the same field of research as Ezzati et al. (2003), Kovats et al. (2005) use comparative risk assessment (CRA) techniques to quantify the avoidable deaths and diseases.[2] The authors consider the WHO 2004 estimates and remark that to generate consistent estimates the models need to incorporate: geographical variation in the vulnerability to climate; future changes in the disease rates due to factors other than climate (e.g. decreases rates of infectious diseases due to technological advances); assumptions on a country's ability to control a disease such as malaria, dengue fever or diarrheal disease; uncertainties around the exposure-response relationship. Moreover, they claim that even controlling for the above mentioned (potentially positive or negative) issues, no model can take into account the possibility of irreversibility or plausible low

[2] The comparative risk assessment approach has been developed in the late 90s by the WHO with aim of estimating the contribution of that different public health factors make to the global burden of diseases. The CRA is based on the following data for each risk factor: *i)* the current and predicted risk distribution of the risk factor; *ii)* the exposure-response relationship of the associated disease; *iii)* the total burden of diseases (e.g. DALYs) lost to the various diseases associated with the risk factor. The proportion of the total burden of a disease that is attributable to e specific risk factor is called Impact Fraction and is defined as:

$$IF = \frac{\sum P_i RR_i - \sum P_i^{'} RR_i}{\sum P_i RR_i}$$

where P_i is the proportion of population in the exposure category, $P_i^{'}$ is an alternative proportion and RR_i is the relative risk exposure at category *i* compared to the reference level.

probability events with potentially high impact on human health. As a main consequence, threshold health effects to regulate “tolerable” amount of climate change cannot be identified.

Finally, Hijioka et al. (2002) relate water-borne diseases with temperature in 14 world regions, showing that the disease incidence tends to increase with temperature. They use multiple regression analysis and include the effect of water supply and sanitation coverage, annual average temperature and per capita GDP, taking into account different IPCC climate scenarios. The results show large regional differences in the impacts.

3.2. Focus: quantitative studies of the relationship between climate change and malaria

3.2.1. Time series studies

Various time series studies explore the relationship between average temperatures, mid-night temperatures, temperatures in conjunction with rainfall rates, as well as November and December temperatures on malaria. In particular, Freeman and Bradley (1996), Freeman (1995), Tulu (1996), Loevinsohn (1994), Bouma et al. (1996) find a significant impact of climate on malaria in Zimbabwe, the Debre Zeit sector of Ethiopia, Rwanda, and the Northwest Frontier Province in Pakistan, respectively. December temperatures coupled with humidity are used by Bouma et al. (1996) to predict incidence rates of malaria in Pakistan. Other studies consider temperature and deforestation in Tanzania (Matola et al., 1987) and Kenya (Malakooti et al., 1997). According to the latter study forest clearing has been the cause for increases in malaria transmission. Kenya is considered also by Patz et al. (1998). The main findings of the article are that soil moisture correlates with the human-biting rate of mosquito vectors with a two-week delay. Also soil moisture and entomological inoculation rate[3] are related, with infective parasites taking a six-week time to develop.

It has been hypothesized that increasing temperatures could be part of the reason why malaria can now survive at higher altitudes. Many other confounding factors, however, could be causing the increase in malaria in these areas (Patz and Lindsay, 1999). The dynamics of the geographical spread of malaria are analyzed by Pascual et al. (2006). The authors focus on the most important malaria species for humans, *Plasmodium falciparum* and *Plasmodium vivax*, whose range is limited at high altitudes by low temperatures. They investigate whether global warming could drive the geographical spread of the disease and produce an increase in incidence at higher-altitude sites. They use data for four high-altitude sites in East Africa in from 1950 to 2006. A nonparametric analysis that decomposes the variability in the data into different components is performed and reveals that the dominant signal in three of the sites and the subdominant signal in the fourth one correspond to a warming trend. To assess the biological significance of this trend, the authors drive a dynamical model for the population dynamics of the mosquito vector with the temperature time series and the corresponding detrended versions. This approach suggests that the observed temperature changes would be significantly amplified by the mosquito population dynamics with a difference in the biological response at least one order of magnitude larger than that in the environmental variable. By using parametric models they also find the existence of significant (linear) trends.

Shanks et al. (2002) investigate whether the reemergence of malaria in Western Kenya could be attributed to changes in meteorological conditions. The existence of trends in a continuous 30-year monthly malaria incidence dataset (1966–1995) is tested for. Malaria incidence increased significantly (p=0.0133) during the 1966–1995 period. In contrast, no aspect of climate is found to have changed significantly-neither the temperature extremes (maximum and minimum) nor the periods when meteorological data were transformed into months when malaria transmission is possible. Therefore, the authors conclude that climate changes have not caused the highland malaria

[3]Entomological inoculation rate is the product of the human-biting rate and the proportion of female mosquitoes carrying infective parasites in their salivary glands ready to be delivered to the next host.

resurgence in western Kenya. Moreover they suggest that two other factors may have influenced the increase in malaria hospitalizations: an increase in malaria severity indicated by an increased case-fatality rate (from 1.3% in the 1960s to 6% in the 1990s) that is most likely linked to chloroquine resistance. Secondly, travel to and from the Lake Victoria region by a minority of the tea estate workers also exerts an upward influence on malaria transmission in Kericho, Kenya, since such travel increases the numbers of workers asymptomatically carrying gametocytes, which infect.

3.2.2. Cross-section and panel data analyses

The spatial variation of malaria is analyzed by Kazembe et al. (2006), who examine malaria-related hospital admissions and in-hospital mortalities among children in Africa. The authors apply spatial regression models to quantify the spatial variation of the two outcomes. Using pediatric ward register data from Zomba district, Malawi, between 2002 and 2003, as a case study, they develop two spatial models. The first is a Poisson model applied to analyze hospitalization and minimum mortality rates, with age and sex as covariates. The second is a logistic model applied to individual level data to analyze case-fatality rate, adjusting for individual covariates. The results show that rates of hospital admission and in-hospital mortality decrease with age. Case fatality rate is associated with distance from the hospital, age, wet season, and increases if the patient is referred to the hospital from the primary health facilities. Furthermore, death rates are high on the first day, followed by relatively low rates as the length of hospital stay increases. The outcomes show substantial spatial heterogeneity, which may be attributable to the varying determinants of malaria risk, health services availability and accessibility, and health seeking behavior. Moreover, the increased risk of mortality of referred children may imply inadequate care being available. The authors suggest that reducing the burden of malaria requires integrated strategies that encompass availability of adequate care at primary facilities, introduce home or community case management and encouraging early referral. Those interventions would be needed to interrupt malaria transmission.

In a subsequent article, Kazembe (2007), the author extends the analysis of Kazembe et al. (2006) to profile spatial variation of malaria risk and analyze possible association of disease risk with environmental factors at sub-district level in northern Malawi. Using the same data on malaria incidence the author compares Bayesian Poisson regression models assuming different spatial structures. For each model he adjusts for environmental covariates initially identified through bivariate non-spatial models. The model with both spatially structured and unstructured heterogeneity is shown to provide the best fit, based on models comparison criteria. Malaria incidence appears to be associated with altitude, precipitation and soil water holding capacity. The risk increases with altitude (relative risk (RR): 1.092, 95% interval: 1.020, 1.169) and precipitation (RR: 1.031, 95% interval: 0.950, 1.120). At medium level of soil water holding capacity relative to low level, the risk is reduced (RR: 0.521, 95% interval: 0.298, 0.912), while at high level of soil water holding capacity relative to low level the risk is raised (RR: 1.649, 95% interval: 1.041, 2.612). Compared to the commonly used standardized incidence ratios, the model-based approach appears to provide homogenous and easy to interpret risk estimates. Generally, the smoothed estimates show less spatial variation in risk, with slightly higher estimates of malaria risk (RR > 1) in low-lying areas mostly situated along the lakeshore regions, in particular in Karonga and Nkhatabay districts, and low risk (RR < 1) in high-lying areas along Nyika plateau and Vwaza highlands. The results suggest that the spatial variation in malaria risk in the region is a combination of various environmental factors, both observed and unobserved. The results also identify what are the areas of increased risk, where further epidemiological investigations could be carried out.

Another interesting study in this context is the one of Bhattacharya et al. (2006) who project malaria transmission in new geographical regions in India. According to this study malaria is expected to move from central regions towards South Westerns and Northern Regions by 2050. Some studies about malaria also project a shift in the duration of transmission windows which might increase or decrease according to the different climatic conditions of a region (Bhattacharya et al., 2006; Dhiman et al., 2008).

Lindsay and Martens (1998) consider the progressive rise in the incidence of malaria over the last decades in African highlands. The phenomenon is largely a consequence of agroforestry development, and is exacerbated by scarce health resources. Moreover, in these areas where the pattern of malaria is unstable, epidemic may be precipitated by relative subtle climate changes and therefore requires special monitoring. The authors use mathematical models to identify epidemicprone regions in highlands Africa, and to quantify the difference expected to occur as a consequence of projected global climate change. To make estimates about the areas that are vulnerable to epidemic outbreaks of malaria, they use data and models from Geographic Information Systems (GIS) (computerized mapping systems) and Remotely Sensed (RS) imagery data from earth-orbiting satellites. Correlations among variables are found. However, the authors observe that since correlation doesn't imply causality these results are not conclusive and require further investigation. To model the dynamics in highlands malaria in relation to climate change they use an integrated system, scenario-based approach (Integrated Assessment Models, see among others, Martens, 1998b and Stern, 2007). Evidence is found that the direct influence of climate may contribute to malaria risk. However, this effect cannot be claimed to be the be the most important determinant of malaria transmission. The effects of temperature on mosquito development, feeding frequency, longevity and incubation period are estimated. The model is linked to baseline climatology data from 1931 to 1960 and uses integrated techniques to generate climate scenarios. Their findings suggest that is not possible to prove that any single factor has caused the outbreaks in African highland. Projected climate changes are likely to modify the epidemics in the regions: 260–320 million more people are projected to be affected by malaria by 2080 as a consequence of new transmission zones.[4]

3.2.3. General equilibrium models

Martens (1998a) proposes a system-oriented analysis, based of scenarios of projected temperatures, and that considers joint effects (rather then phenomena in isolation) to assess the future impacts of climate change. In his analysis he considers the effects of climate change on vector-borne diseases, on thermal-related mortality, and the effects of increasing ultra-violet levels due to ozone depletion on skin cancer. Considering malaria the author defines the basic reproduction rate in an area (R_0) as

[4] The study of Lindsay and Martens (1998) as well as Shanks et al. (2002) and Pascual et al. (2006) analyze the (re)emergence of malaria in regions once free of this disease risks. These contribution add to a vast literature on the epidemics of malaria. This includes: studies of the highlands of Kenya, Madagascar, Burundi and Irian Jaya, Indonesia (Kigotho 1997; Khaemba et al., 1994; Fontaine et al., 1961; de Zulueta, 1994; Fontenielle et al., 1990; Mouchet et al., 1997; Marimbu et al., 1993; Anthony et al., 1992; Bangs et al., 1995). Other analyses include the study of Freeman (1994) and Woube (1997) on epidemics in Manyuchi dam, Zimbabwe and Ethiopia, respectively.

the vector capacity multiplied by the duration of the infectious period in humans. The factors that are involved in the calculation of (R_0) include: the mosquitoes/people ratio, the number of mosquito bites per person per day, the probability that an infected mosquito infects a human, the chances that a mosquito becomes infected during a blood meal, the incubation period, and the daily survival probability of the mosquito. Indirect factors that affect the ones that are listed above include: the availability of breeding sites which is related to precipitation, human population density, human population migration, the feeding habits of the mosquitoes, the presence of other animals on which the mosquitoes feed, human exposure which can be affected by the use of bednets or other interventions, temperature the immunological and nutritional status of the population, the effectiveness of medical treatment, natural enemies of the mosquitoes, and control efforts. This model is further complicated by algorithms that predict changing genetic adaptations in the parasite and vector that lead to resistance. Based on this approach, evidence is found that the number of people in developing countries likely to be at risk of malaria infection will increase by 5-15% because of climate change, depending on which the Global Circulation Model (GCM) and climate change scenario is used. The areas that are expected to have the most increase in malaria transmission are ones at the fringes of transmission. Unless they are able to use effective control strategies, these regions have low levels of immunity and are likely to experience epidemics (Martens, 1998a).

In general, there is considerable uncertainty about the magnitude of the overall impact of malaria. While some models project a net increase in the population exposed to malaria (and in the incidence rate) due to climate change (Martens et al., 1995), others have found only minor changes in malaria distribution (WHO, 2003 - McMichael et al.). This uncertainty is due to the complex dynamics underlying the transmission of this vector and to other important factors such as the socio-demographic and environmental factors which are playing a substantial role in the transmission mechanism.

3.3. General studies

The previous section has concentrated on recent quantitative contributions on the relationship between climate and health. Since this issue involves many disciplines and view points, however, more extensive outlooks become necessary, as they provide a framework for understanding the interactions between climate and health in a broader perspective. A summary of the main reports and of the specific findings and methods therein is presented below.

3.3.1. The economics of climate change

The Stern Report (2007) is a key reference giving a complete framework of the economics of climate change. The book reviews scientific and geological basis of the studies on climate change's impacts. For example, it lists the possible impacts associate to 1°, 2° up to 5°C of temperatures increases. Restricting to the effects for health, these include a larger (and increasing exponentially with temperatures) number of deaths caused by diseases such as malaria, diarrhea and malnutrition at lower latitudes (Africa); and a reduction in winter deaths at higher latitudes (Northern Europe, USA). The author considers the ethical implications of the disproportionate distributions of impacts across regions and populations, and provides a series of policy indications. For the problem at stake, the chapter that concerns the economic analyses of climate change costs is specifically relevant.

The measurement of costs of climate (measured on income/consumption, health and environment dimensions) is a challenging task. The main reasons being that this kind of analyses involves the use of variables and projections that are highly uncertain (however, according to the author, omitting some of uncertain but potentially most damaging impacts have caused some early attempts to underestimate the costs of climate change). Moreover, the effects can be seen only over several decades and with a long-time delay. Based on a review of the studies of the costs of climate warming, the author concludes that the Integrated Assessment Models (IAM) constitute a valid methodological foundation; however first-round IAM studies consider the effects of climate at temperatures that are now likely to be exceeded. The mixed evidence found by different authors crucially relies on what increase in temperature is considered. Indeed, there is a common evidence that the warming above 3-4°C would reduce global welfare, and that and temperatures increases of 5-6°C can be estimated to be equivalent to a 5%-10% reduction in global GDP in the "no-climate-change" scenario.

In the methodological framework of IAM, Stern estimates the BAU (business as usual) costs of climate: he estimates the costs to be equivalent of a per-capita reduction of income of 5% at minimum. This proportion could increase to 11% by considering the direct effects on environment and health ("non-market" impacts).[5] In case it turns out to be true that the responsiveness of climate system to gas emissions is larger than what previously thought, the costs would increase even more. Finally there is a noticeable disproportion in the distribution of the burden of climate change impact among developing and rich countries. As regards health, the major impacts are expected in countries such as Sub-Saharan Africa and Asia, which are already facing a considerable burden of disease. Developing countries are actually tackling with more constraints. On the one hand they are expected to face high population growth with increased risk of poor housing, hunger and infectious diseases due to poor water and sanitation systems. On the other hand, their adaptive capacity is limited in terms of financial and infrastructural resources, health care system, poor health status of the population and poor capacity of collecting and analyzing data. Additional problems are related to income inequalities, migration and conflicts. As stated in the last IPCC report (IPCC, 2007), priorities for research should include the development of methods to provide more quantitative assessments of climate change impacts in low- and middle-income countries.

[5] The total damage evaluated in terms of loss of life caused by climate change is estimated to range from US$ 6 billion to US$ 88 billion (1990 dollar prices) (IPCC, 2007). In terms of disability adjusted life years (DALYs) the loss has been estimated around 5.5 million in year 2000 (Lancet and the University College London Institute for Global Health Commission, 2009).

3.3.2. Managing the health effects of climate change

Managing the Health Effects of Climate Change is a wide multidisciplinary overview of the major threats - both direct and indirect - to global health from climate change, carried on by Lancet and University College London Institute for Global Health Commission (2009). Effects of predicted climate change are described by the authors and actions to be undertaken are discussed.

The starting point of the analysis is that during this century, earth's average surface temperature rises are likely to exceed the safe threshold of 2°C above preindustrial average temperatures. Rises will be greater at higher latitudes, with medium-risk scenarios predicting 2–3°C rises by 2090 and 4–5°C rises in northern Canada, Greenland, and Siberia.

Health effects of the predicted climate change will cause vector-borne diseases to expand their reach and death tolls, especially among elderly people, moreover the indirect effects of climate change on water, food security, and extreme climatic events are likely to have the biggest effect on global health.

An integrated and multidisciplinary approach to reduce the adverse health effects of climate change requires at least three levels of action. First, policies must be adopted to reduce carbon emissions and to increase carbon biosequestration, and thereby slow down global warming and eventually stabilize temperatures. Second, further research is needed to understand clearly the links between climate change and disease occurrence. Third, appropriate public health systems should be put into place to deal with adverse outcomes in terms of efficient and cost-effective adaptation measures at local, and national levels.

The UCL Lancet Commission considers what the main obstacles to effective adaptation might be, focusing on six aspects that connect climate change to adverse health outcomes: changing patterns of disease and mortality, food, water and sanitation, shelter and human settlements, extreme events, and population and migration. Each is considered in relation to five key challenges to form a policy response framework: informational, poverty and equity-related, technological, sociopolitical, and institutional.

Our capacity to respond to the negative health effects of climate change relies on the generation of reliable, relevant, and up-to-date information. Strengthening informational, technological, and scientific capacity within developing countries is crucial for the success of a new public health movement. This capacity building will help to keep vulnerability to a minimum and build resilience in local, regional, and national infrastructures.

Few comprehensive assessments on the effect of climate change on health have been completed in low-income and middle-income countries, and none in Africa. The report endorses the 2008 World Health Assembly recommendations for full documentation of the risks to health and differences in vulnerability within and between populations; development of health protection strategies; identification of health co-benefits of actions to reduce greenhouse gas emissions; development of ways to support decisions and systems to predict the effect of climate change; and estimation of the financial costs of action and inaction. Policy responses to the public health implications of climate change will have to be formulated in conditions of uncertainty, which will exist about the scale and timing of the effects, as well as their nature, location, and intensity.

A key challenge is to improve surveillance and primary health information systems in the poorest countries, and to share the knowledge and adaptation strategies of local communities on a wide scale. Essential data need to include region-specific projections of changes in health-related exposures, projections of health outcomes under different future emissions and adaptation scenarios, crop yields, food prices, measures of household food security, local hydrological and climate data, estimates of the vulnerability of human settlements (e.g., in urban slums or communities close to coastal areas), risk factors, and response options for extreme climatic events, vulnerability to migration as a result of sea-level changes or storms, and key health, nutrition, and demographic indicators by country and locality.

In the view of the commission the key factors to management of health effects of climate change will be: reduction of poverty and inequity in health; incentives for the development of new technologies and application of existing technologies in developing countries; change in lifestyle; improved coordination and accountability of global governance; increase advocacy to reduce climate change trough public health awareness.

3.3.3. Developing diseases and Early Warning Systems

Early Warning Systems (EWS) related to infectious diseases are discussed in the World Health Organization's paper by Kuhn et al. (2005).

This WHO report presents a framework for developing disease EWS. It then reviews the degree to which individual infectious diseases are sensitive to climate variability in order to identify those diseases for which climate-informed predictions offer the greatest potential for disease control. The report highlights that many of the most important infectious diseases, and particularly those transmitted by insects, are highly sensitive to climate variations.

Subsequent sections review the current state of development of EWS for specific diseases and underline some of the most important requirements for converting them into operational decision-support systems.

Considerable research is currently being conducted to elucidate linkages between climate and epidemics. Of the 14 diseases meeting the defined criteria for potential for climate-informed EWS, few (African trypanosomiasis, leishmaniasis and yellow fever) are not associated with some sort of EWS research or development activity. For West Nile virus, an operational and effective warning system has been developed which relies solely on detection of viral activity and it remains unclear whether the addition of climatic predictors would improve the predictive accuracy or lead-time. For the remaining diseases (cholera, malaria, meningitis, dengue, Japanese encephalitis, St Louis encephalitis, Rift Valley Fever, Murray Valley encephalitis, Ross River virus and influenza), research projects have demonstrated a temporal link between climatic factors and variations in disease rates. In some of these cases the power of climatic predictors to predict epidemics has been tested.

The research reviewed in this report demonstrates that climate information can be used to improve epidemic prediction, and therefore has the potential to improve disease control. In order to make full use of this resource, however, it is necessary to carry out further operational development. The true value of climate-based early warning systems will come when they are fully integrated as one component in well-supported systems for infectious disease surveillance and response. The report concludes that a number of steps could be taken to begin to address these issues. These include:

- Maintaining and strengthening disease surveillance systems for monitoring the incidence of epidemic diseases;
- Clarifying definitions of terminology and methods for assessing predictive accuracy;
- Testing for non-climatic influences (e.g. population immunity, migration rates and drug resistance) on disease fluctuations is dependent on the availability of appropriate data;
- Distinguishing underlying trends from interannual variability should help to avoid disease variations being attributed incorrectly to climate. More important, in practical terms, incorporating the data available for non-climatic variables should lead to greater accuracy in predictive models.

3.3.4. Evaluating the risks to human health related to climate change

The 2003 report entitled "Climate Change and Human Health – Risk and Responses", prepared jointly by the WHO, the World Meteorological Organization and the UNDP, provides a comprehensive update, including quantitative estimates of the total health impacts of climate change and identifies the steps necessary to further scientific investigation and to develop strategies and policies to help societies adapt to climate change.

Monitoring and surveillance systems, in many parts of the world, currently are unable to provide data on climate-sensitive diseases that are sufficiently standardized and reliable to allow comparisons over long time periods or between locations. Current research gaps include the need for more standardized surveillance of climate-sensitive health states, especially in developing countries. The assessment of climate change impacts on human health depends strongly on the availability of reliable health data to be linked with climate data, requiring measurements at local level which are often not feasible in developing countries.

Methods and tools for monitoring the effects of climate change on human health and for predicting future effects are discussed in several parts of the book.

Predicting modeling approaches are classified into several categories including:

- Statistical based models – empirical models incorporating a range of meteorological variables have been developed to describe the climatic constraints (the bioclimate envelope) for various vector-borne diseases (CLIMEX; DIMEX; GCMs);

- Process-based (mathematical) models – process-based approach is important in climate change studies as some anticipated climate conditions have never occurred before and cannot be empirically based (i.e. MIASMA);

- Landscape-based models – climate influences the habitat of pathogens and diseases vectors. There is a potential in combining climate-based models with the various environmental factors that can be measured by ground-based or remote sensing, including satellite data;

- Predictive models for early warning systems (EWS).

Exposure to climate change is estimated by predicting changes in global climate conditions for specific locations. In the current models all the population is considered as exposed. The risk of suffering health impacts also will be affected by sociodemographic conditions and other factors (e.g. environmental conditions and ecological influences) affecting vulnerability. Such variations are considered in the calculations of relative risk for each disease. The choice of the modeling approach depends on the availability of high resolution data on health states and the possibility of estimating results that comply with the framework of the overall Comparative Risk assessment.

Distinction is made between epidemiological methods and health impact assessment methods. Current epidemiological research methods are best able to deal with the health impacts of short-term (daily, weekly, monthly) variability, which require only a few years of continuous health data.

In contrast, health impact assessment methods address the application of epidemiological functions to a population to estimate the burden of disease. Attributable burdens can only be estimated for those weather-disease relationships for which epidemiological studies have been conducted. The available evidence indicates that weather-disease relationships are highly context specific and vary between populations; therefore such models need to be derived from site specific data.

A detailed methodology for the quantification of the health impacts of climate change at national and local levels is provided by Campbell-Lendrum and Woodruff (2007), including the following steps: identification of climate scenarios, measurement of population exposure, quantification of the linkage between climate variables and specific health outcomes, combination of climate projections and quantitative health models, estimation of the health impacts in the absence of climate change and estimation of the climate attributable factor for each disease.

In general predictive modeling need for a multidisciplinary integrated assessment, integration between sectors, integration across the regions and the assessment of adaptation.

A broad range of data is needed to monitor climate effects on health. Where possible monitoring systems should assemble data on all components required for statistical analysis (including assessment of health modification) or process-based biological models. Relevant measurements fall into the following broad classes:

- Meteorology: various meteorological factor influence heath processes. Temperature, relative humidity, rainfall and wind speed are the most important parameters;

- Health markers: one way to address the complex causality of most health outcomes is to select indicators that are highly sensitive to climate changes, but relatively insensitive to other influences. The data requirements for attributing and measuring impacts may be quite different, depending on health issue and region. For studies of direct effects of health and cold the essential requirements is daily series of counts of death and mobility divided by age and cause, but where the intention is to look at health effects resulting from complex ecological processes, such as infectious diseases transmitted through food water or vectors, the data requirement become more complex;

- Other explanatory factors: monitoring will need to measure not just climate and health. The principal categories of modifying factors that must be considered are the following: age structure of population at risk; underlying rate of disease; level of socio economic development and existing infrastructures (water and sanitation); environmental conditions, quality of health care; specific disease control measures.

3.3.5. Modifiable environmental risk factors

Of specific interest is the study on modifiable environmental risk factors (Prüss-Üstün and Corválan, 2006) again published by the World Health Organization. The analysis is conducted with reference to 85 categories of diseases and is quantified in terms of "disability adjusted life years" (DAILY)s. The effects of risk factors' reductions are evaluated in terms of reductions in diseases and related costs of the health–care system.

The definition of environmental factors includes man-made climate changes, pollution etc. and all the related behavioral and socio-economical consequences. For each environmental risk factor the "attributable fraction" of disease is defined. The "attributable fraction" is the decline in disease or injury that would be achieved in a given population by reducing the risk (see note 1 of the previous section for a formal definition). When calculating the disease burden attributable to an environmental risk factor the analyses consider how much disease burden would decrease by reducing risk to an achievable level. The environmental fraction is a mean value and it is not necessarily applicable to an individual countries. The analysis uses data from the Comparative Risk Assessment (CRA) (WHO, 2002) and estimates for specific environmental factors not covered by the CRA.

The authors estimate that 24% of the global disease burden and 23% of all deaths can be attributed to environmental factors. Among children 0–14 years of age, the proportion of deaths attributed to the environment is as high as 36%. There are large regional differences in the environmental contribution to various disease conditions – due to differences in environmental exposures and access to health care across the regions. For example, although 25% of all deaths in developing regions are attributable to environmental causes, only 17% of deaths are attributed to such causes in developed regions. Moreover it is worth noting that this is a conservative estimate because there is as yet no evidence for many diseases. Also, in many cases, the causal pathway between environmental hazard and disease outcome is complex. Some attempts are made to capture such indirect health effects. For instance, malnutrition associated with waterborne diseases is quantified. But in other cases, disease burden is not quantifiable even though the health impacts are readily apparent. For instance, the disease burden associated with changed, damaged or depleted ecosystems in general is not quantifiable.

Diseases with the largest absolute burden attributable to modifiable environmental factors includes: diarrhea; lower respiratory infections; 'other' unintentional injuries; and malaria.

- **Diarrhea.** An estimated 94% of the diarrheal burden of disease is attributable to environment, and associated with risk factors such as unsafe drinking-water and poor sanitation and hygiene;

- **Lower respiratory infections.** These are associated with indoor air pollution related largely to household solid fuel use and possibly to second-hand tobacco smoke, as well as to outdoor air pollution. In developing countries an estimated 42% (95% confidence interval: 32 -47%) of such infections are attributable to environmental causes. In developed countries, this rate is about halved to 20% (15-25%);

- **'Other' unintentional injuries.** These include injuries arising from workplace hazards, radiation and industrial accidents; 44% of such injuries are attributable to environmental factors;

- **Malaria.** The proportion of malaria attributable to modifiable environmental factors is 42%, or half a million deaths annually. Policies and practices regarding land use, deforestation, water resource management, settlement siting and modified house design, e.g. improved drainage could prevent almost half of malaria incidence. The fraction amenable to environmental management, however, varies slightly depending on the region.

The large disproportions across regions and populations of the burden of diseases attributable to environmental factors give rise to ethical considerations and the need for policy measures. Public preventive health strategies are economically competitive with more traditional curative health-sector interventions. As an example, phasing out leaded gasoline can be mentioned. Indeed, estimates report that mental retardation is 30 times higher in regions where leaded gasoline is still being used. The authors recommend that policy regulations should include reducing the disease burden due to environmental risk factors as a way to eradicate extreme poverty and promote equality.

4. Conclusions

This paper has focused on the critical evaluation of recent quantitative assessments of health risks associated with climate change. The main contribution of our paper is to offer an integrated vision of the main scientific conclusions on the effects of climate change on human health, which are supported by the use of formal qualitative analyses.

In this respect, the journal articles surveyed in this paper have been classified according to: *i*) the statistical models adopted, which have been identified in the broad classes of time-series models, cross-section and panel analyses, equilibrium models and various other techniques; ii) the specific problems addressed, which have been referred to as primary studies, secondary studies and comparative risk assessments.

As far as more extensive reports on this subject are concerned, this specific classification has been found difficult to apply, since several contributions of this kind compare analyses of different types and methods. Therefore, we have chosen to avoid any predetermined classification, and to concentrate on the relevant findings of each outlook.

Climate change is already affecting human health, livelihoods, safety, and society and the expectation is that these effects will become greater. The climate impact is still difficult to assess with great accuracy because it results from a complex interplay of factors. It is challenging to isolate the human impact of climate change definitively from other factors such as natural variability, population growth, land use and governance. In several areas, the base of scientific evidence is still not sufficient to make definitive estimates with great precision on the human impacts of climate change. However, data and models do exist which form a robust starting point for making estimates and projections that can inform public debate, policy-making and future research. Climate change aggravates existing problems, e.g. seasonal rainfall leading to floods or water scarcity during extended droughts. Climate change acts as a multiplier of these existing risks.

For example, as the international community struggles to reduce hunger-related deaths, a warmer, less predictable climate threatens to further compromise agricultural production in the least developed countries, thereby increasing the risk of malnutrition and hunger. Think of a region suffering from water scarcity. That scarcity reduces the amount of arable land and thereby aggravates food security. The reduced crop production results in loss of income for farmers and may bring malnutrition. Health issues arise that could further diminish economic activity as family members become too weak to work.

The definition of "being seriously affected" by climate change includes someone in need of immediate assistance in the context of a weather-related disaster or whose livelihood is significantly compromised. This condition can be temporary, where people have lost their homes or been injured in weather-related disasters, or permanent, where people are living with severe water scarcity, are hungry or suffering from diseases such as diarrhea and malaria. Below we give the current best estimates of the level of impact of climate on health and likely trends in those impacts.

An estimated 325 million people are seriously affected by climate change every year. This estimate is derived by attributing a 40% proportion of the increase in the number of weather-related disasters from 1980 to current climate change and a 4% proportion of the total seriously affected by environmental degradation based on negative health outcomes.

Gradual environmental degradation due to climate change has also affected long-term water quality and quantity in some parts of the world, and triggered increases in hunger, insect-borne diseases such as malaria, other health problems such as diarrhea and respiratory illnesses. It is a contributing factor to poverty, and forces people from their homes, sometimes permanently.

Intuitively, if someone is affected by water scarcity, poverty or displacement, this also translates into health outcomes and food insecurity. Typically, climate change today mostly affects areas already seriously suffering under the above mentioned factors. Likewise, health outcomes and food insecurity lead to displacement and poverty which might result in competition for scarce resources and strains on mostly already limited government capacity to deal with deteriorating conditions and might ultimately lead to conflict. Therefore health outcomes and food security are taken as the basis for all climate change related impacts. Using this approach, the update of WHO Global Burden of Disease study shows that long term consequences of climate change affect over 235 million people today.

Global warming is expected to increasingly impact food security, water availability and quality, and exact a toll on public health, spurring chronic disease, malaria prevalence, and cardiovascular and respiratory diseases.

Current weather conditions heavily impact the health of poor people in developing nations, and climate change has a multiplying effect. A changing climate further affects the essential ingredients of maintaining good health: clean air and water, sufficient food and adequate shelter. A warmer and more variable climate leads to higher levels of some air pollutants and increases transmission of diseases through unclean water and contaminated food. It compromises agricultural production in some of the least developed countries, and it increases the hazards of weather-related disasters.

Therefore global warming, together with the changes in food and water supplies it causes, can indirectly spurs increases in such diseases as malnutrition, diarrhea, cardiovascular and respiratory diseases, and water borne and insect-transmitted diseases. This is especially worrisome because a massive number of people are already impacted by these diseases - for example upwards of 250 million malaria cases are recorded each year and over 900 million people are hungry today. Also, there is an inter-relationship among these health outcomes. For example malnutrition is linked with malaria and diarrhea which can cause significant weight loss in affected children when accompanied with food scarcity. Malaria and diarrhea can be both cause and effect of malnutrition.

Malnutrition is the biggest burden in terms of deaths. Climate change is projected to cause over 150,000 deaths annually and almost 45 million people are estimated to be malnourished because of climate change, especially due to reduced food supply and decreased income from agriculture, livestock and fisheries. Climate change-related diarrhea incidences are projected to amount to over 180 million cases annually, resulting in almost 95,000 fatalities, particularly due to sanitation issues linked to water quality and quantity. Climate change-triggered malaria outbreaks are estimated to affect over 10 million people and kill approximately 55,000. Malaria is expected to increase as an effect of increased transmission windows in some regions and because a shift in transmission to new areas is expected.

Over 90% of malaria and diarrhea deaths are borne by children aged 5 years or younger, mostly in developing countries. Other severely affected population groups include women, the elderly and people living in small islands developing states and other coastal regions, mega-cities or mountainous areas. These groups are the most affected due to social factors like gender discrimination, which can restrict women's access to health care, and age-based susceptibility as children and elderly often have weaker immune systems. Additionally, people living in certain geographic areas are more affected due factors such as high exposure to storms along coastlines, inadequate urban planning etc. Almost half the health burden occurs in the population dense Southeast Asia region with high child and adult mortality, followed by losses in Africa (23%) and the Eastern Mediterranean region. Overall, the per capita mortality rate from vector borne diseases (diseases like malaria that are transmitted by insects) is almost 300 times greater in developing nations than in developed regions (14%).

The pressure for increased precision in estimates presents a rallying cry for investment in research on the social implications of climate change. Three areas which require additional research have been identified:

- The attribution of weather-related disasters to climate change, as no consensus estimate of the global attribution has yet been made;
- Estimate of economic losses today, as the current models are forward looking;
- Regional analysis, as the understanding of the human impact at regional level is often very limited but also crucial to guide effective adaptation interventions.

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Part IV

Conclusion

In this Thesis I have dealt with econometric models for electricity demand, power prices and the effects of climate change on health. In the first two chapters I have tried to find out what approach is more suitable for analyzing electricity markets, and to quantify how the use of sophisticated methods can enhance the results. The third chapter reviews recent quantitative contributions on the health effects of climate change and provides a taxonomy of the adopted methodologies. The empirical results of the first Chapter have shown that using Bayesian techniques and allowing the coefficients to evolve over time improve the in-sample analysis of Italian electricity demand, but it does not increase the accuracy of out-of-sample forecasts. In Chapter II it has been shown that adopting non-linear model based on threshold cointegration is opportune for investigating the integration of European forward markets. Chapter 3 has evidenced that data and models do exist; however there is a lack of consensus about the attribution of weather-related disasters to climate change, the economic costs (benefits) of climate change, the assessments of effects at regional level. Further research can be suggested by these results. For the analysis of the electricity system it can consist in investigating whether a further extension of models' flexibility can improve their forecasting performances. As for the analysis of the climate change effects on health my study can provide the basis for developing new investigation methods.