Eco-label Adoption in an Interdependent World

Monteiro, Jose-Antonio

University of Neuchâtel

January 2010

Eco-label Adoption in an Interdependent World*

José-Antonio Monteiro†

First Draft: January 2010

Abstract

The growing popularity of national efforts to promote eco-labeling raises important questions. In particular, developing countries fear that the eco-label can deliberately impose the environmental concern of (high income) importing countries on their production methods. Yet, empirical studies of the adoption of eco-labelling schemes at the cross-country level are scarce due to the lack of data availability. In this paper, the decision to introduce an eco-label is analyzed through a heteroskedastic Bayesian spatial probit, which allows the government's decision to introduce an eco-label to be influenced by the behaviour of the neighbouring countries. The estimation is performed by extending the joint updating approach proposed by Holmes & Held (2006) to a spatial framework. Empirical evidence highlights the importance of a high stage of development, innovation experience and potential scale effects in the implementation of an eco-label scheme. In addition, results confirm the existence of a strategic interdependence in the eco-label decision.

Keywords: Bayesian Spatial Probit, International Trade, Environmental Policy

JEL classification: F18, F23, Q56, C31, C33

*I am grateful to Sana el Harbi for providing me with additional information on the different eco-labels across the world.

†PhD Student, University of Neuchatel, jose-antonio.monteiro@unine.ch

1 Introduction

"Eco-labels" is the short form for ecological labels. They contain information regarding potential impacts on the environment of the production, consumption and waste phases of the products/services consumed. However, eco-labelling schemes are not just messages about a product or a service but claims stating that it has particular properties or features (Mason, 2006). In fact, even the instrument of labelling itself is a claim, as it refers to certain characteristics of the procedure under which the label is awarded. The very own existence of eco-labels arises when firms have information on the environmental impact of the product that consumers value but cannot check. Buyers are unable to verify the environmental consequence of the goods before the purchase or through frequent purchase. This type of information asymmetry, also known as credence feature, is due to the temporal, spatial and non-exclusion characteristics of most environmental impacts. In addition, the environmental degradation (or improvement) generated by the environmental characteristics of the conventional (or eco-friendly) product displays properties of public goods showing either non-excludability or non-rivalry in the consumption. This usually implies a free riding problem as well as an assurance problem. Moreover, no market prices prevail to really reflect the value of the production and consumption externalities of the product. These public good features lead to a misallocation of scarce resources because the decision-making process does not take into account all the costs.

According to the International Organization for Standardization (ISO), the type of eco-labelling considered in this study is called type I labels[1]. This category of eco-labels is owned and operated by third parties, which may be governmental organizations or private non-commercial entities, and is awarded for products and manufacturing processes which meet certain environmental criteria. The firm's participation is completely voluntary. Indeed, manufacturers must pay for the right to display the label and demonstrate continued adherence to relevant product guidelines to maintain their certifications. This type of market based instruments seeks to fulfill two objectives:

1. provide consumers with more information about the environmental effects of their consumption, (i.e. transform the product's credence attribute into a search attribute), which should generate a move towards more environmentally friendly consumption patterns;

[1]ISO distinguishes two additional categories of ecolabels. Type II is associated with informative environmental self-declaration claims which are not verified by any independent third party. Type III covers voluntary programs that provide quantified environmental data of a product, under pre-set categories of parameters set by a qualified third party and based on life cycle assessment, and checked by that or another qualified third party.

2. encourage economic agents (mainly firms and governments) to increase the environmental standards of products/services by benchmarking environmental performance (i.e. internalize the non-market benefits of the eco-labelled good).

While most industrialized countries have adopted an eco-labelling scheme, African and Latin American countries have yet to decide to implement this type of market-based initiative. This very unequal diffusion among countries has received considerable attention in the World Trade Organization (WTO). Although WTO rules exclude trade policy measures based solely on different process and production methods, eco-labels are criticized for potentially imposing the environmental concerns of (high income) importing countries on the production methods of (low income) trading partners (Bonsi et al., 2008). If governments consider the eco-label as a strategic environmental policy instrument, the decision to introduce an eco-label will ultimately depend on how many and which countries are expected to adopt an eco-labelling scheme. Thus, a country could deliberately implement this instrument policy in order to protect local industries. Obviously this type of non-tariff barriers to trade is particularly problematic for countries depending heavily on exports.

Despite this concern, most literature on eco-labels and its international trade linkages takes a conceptual or descriptive approach due to the lack of data. To my knowledge, this paper is one of the few to analyze empirically the linkages between eco-labelling and international trade in an interdependent world. To tackle the issue of interdependence, a spatial probit model is estimated using a new Bayesian Markov-Chain-Monte-Carlo algorithm. Following Holmes & Held (2006) I improve the performance of the spatial probit model simulation in terms of mixing and convergence by jointly updating the non spatial regression parameters and the auxiliary variable (i.e. stochastic latent variable whose sign determines the value taken by the limited dependent variable (1 or 0)). As far as I know, this is the first time that this type of joint sampling is done in a spatial Bayesian framework. Empirical evidence confirms the role of the economy's stage of development and innovation capacity in the government's decision to introduce an eco-label. Moreover, results highlight the strategic nature of the eco-labelling decision and a potential substitutive relationship between tariffs and eco-label. These results partially validate the view that the one of the underlying role of the eco-label program might be to act as a technical trade barrier and serve protectionist objectives.

The remainder of the paper is structured as follows. Section 2 provides a theoretical background to eco-labels and their impact on international trade linkages. Section 3 describes the spatial probit model as well as the joint sampling estimation method and its performance in a small Monte-Carlo simulation study. Section 4 reviews the determinants in the eco-label adoption and the empirical results are discussed in section 5. Section 6 checks the robustness of the findings. Finally, section 7 concludes.

2 Eco-label and International Trade Linkages

Although eco-labels based on voluntary Life Cycle Assessment (LCA) are neither covered by the Technical Barriers to Trade Agreement nor by the WTO, developing countries are concerned about the discriminatory effects caused by the implementation of the eco-labels[2]. This issue has been the object of a large theoretical and juridical literature, even before famous trade disputes like the US restrictions on imports of non "dolphin-safe" tuna or "turtle-safe" shrimps. Table 1 highlights the intended as well as unintended effects associated with the introduction of an eco-label.

Table 1: Eco-label's Effects

Intended Effects	**Unintended Effects**
- Green Market Expansion	- Protectionism Abuse
- Environmental Consciousness	- Deterioration of Terms of Trade
- Investment Innovation	- Innovation Distortion
	- Oversupply of Eco-label
	- Free Rider Problem

The launch of an eco-label program is expected to boost export earnings through products differentiation. It may also allow innovative firms to exploit at their fullest environmentally friendly production methods. In developing countries, the introduction of an eco-labelling scheme can potentially offer new opportunities to attract capital investment to expand environmentally sustainable niche market.

[2] The WTO Agreement on Technical Barriers to Trade's preamble states: ... *no country should be prevented from taking measures necessary to ensure the quality of its exports, or for the protection of human, animal or plant life or health, of the environment, or for the prevention of deceptive practices, at the levels it considers appropriate, subject to the requirement that they are not applied in a manner which would constitute a means of arbitrary or unjustifiable discrimination between countries where the same conditions prevail or a disguised restriction on international trade.*

However, unlike safety and health issues that tend to be relatively homogeneous across countries, attitudes toward the environment may differ widely. This can lead to disagreements between countries over the validity of a specific requirement (Beaulieu & Gaisford, 2002). Since demand for environmental quality tends to be income elastic, these differences in attitude are often greatest between high and low income countries. In particular, less developed countries believe that domestic interests mainly dictate the product selection process, and, thus, foreigner producers may be required to meet criteria that are not relevant in their own country. This is particularly problematic for small and medium enterprises in small resources constrained developing countries, as certification procedures and eco-labelling compliance require important funding (Piotrowski & Kratz, 1999). Beside these costs, producers in many low income countries face asymmetric information. They do not necessarily possess information about some eco-label programs and know about all the certification requirements. These obstacles are further exacerbated by the fact that advanced technologies used to define the standards of the eco-label might be patented and thus difficult to access if not unaffordable. This becomes even more problematic when each developed country supports different underlying eco-labelling criteria making it almost impossible for the producers to exploit economies of scales. The cost of complying with each eco-label program can ultimately prevent developing countries to export their products to markets where an eco-label is in place. This is an important issues for countries depending extensively on foreign trade as well as economies which have to determine their strategic trade interests in order to sustain potential economic growth.

Although countries are judicially independent, they are economically interdependent because of international trade. Each government may face strategic interdependence on its national and export markets. Consequently, a country, which faces competitive challenges from a large number of countries whose level of environmental policy differs, will have some incentives to change its environmental regulation in response to other countries' policies. The governmental decision to introduce an eco-labelling program can thus be seen as strategic and depending on the decision of other countries (Basu et al., 2004). Two main related mechanisms can explain the strategic environment in adopting an eco-label. First, a country, which faces competition from importers on its national market, might be willing to introduce an eco-labelling scheme whose criteria may be determined, intentionally or unintentionally, in favour of domestic firms. If domestic producers can adopt the eco-label more easily than foreign firms due to the criteria established, this may cause undesirable trade effects or trade frictions. For instance, the introduction of an eco-labelling program can increase the perceived quality of eligible domestic products and decreases that of noneligible imported product through market signalling[3]. Therefore, one of the "protectionist-like" effects could result from consumers valuing cleaner production, and hence, switching from the imported product to the domestically produced good once the standard becomes known. This change in consumption spending in favour of the eco-label product can lead to a decrease in the price of the eco-label product, which ultimately can reduce the trade volume and worsens the terms of trade of the developing exporters. In addition, the lack of transparency of the LCA process, notification and technical assistance can lead to higher costs of production and operation for the foreigner producers, which ultimately could result in losing competitive advantage (UNEP, 2005). Second, an exporting country, which is interested in extending its foreign market share (presumably to high income countries), might also be interested in adopting an eco-label program. Just like in the first case, it is the determination of the standards associated with the eco-label, rather than the information embodied in it, that explains why eco-labelling affects the market access to (developing) exporters.

Be that as it may, eco-labelling programs might still be a poor substitute for policies such as tariffs, that may be more mandatory, but less WTO compliant. The main reason is that as the number of countries adopting eco-labels increases, existing consumers of eco-labelled products can be tempted to free ride by reducing their own purchases (Mesler & Robertson, 2005). Therefore, it is necessary to consider the extent to which eco-labels and trade restrictions might be substitutable with respect to their impact on the environment in an interdependent world. This is one of the objectives of this paper, which is achieved by estimating a spatial probit model.

3 Joint Sampling in Bayesian Heteroskedastic Spatial Probit Model

Assuming that each country assesses the costs and benefits of adopting an eco-label, a rational government will introduce an eco-labelling scheme only if it gains in welfare, expressed in monetary terms or net gain in utility[4]. Formally, $\mathbf{Y}_i^\star$ denotes country i's welfare associated with the adoption of the eco-label. Note that $\mathbf{Y}_i^\star$ is by definition a latent or auxiliary variable

[3] For instance, the share of eco-labelled paper for notebooks in the swedish and danish market has increased over time to about 80%.

[4] Most theoretical papers focusing on the labelling procedure considers an authority that maximizes a social surplus which depends on the profits of the firms, the consumers' surplus, the environmental damage associated with the production of the good as well as other potential costs related to the introduction of the eco-label (Greaker, 2006).

and thus cannot be observed directly. What is observable is the binary indicator variable $\mathbf{Y}_i$ with entry 1 if the country has adopted an eco-label ($\mathbf{Y}_i^\star > 0$) and 0 otherwise ($\mathbf{Y}_i^\star < 0$). As explained in the previous section, a government's decision to introduce an eco-label may depend on the related decision of other close countries. Yet, assuming incorrectly that the decision of country i is independent of the decision of the $N-1$ remaining countries leads to biased as well as inconsistent and inefficient estimates which voids subsequent hypothesis testing (LeSage & Pace, 2009). That is why the latent variable is specified as a spatial autoregressive probit model[5]:

$$\begin{aligned} \mathbf{Y}^\star &= \rho \mathbf{W} \mathbf{Y}^\star + \mathbf{X}\beta + \mathbf{u} \\ \mathbf{Y} &= \mathbf{1}\left[\mathbf{Y}^\star > \mathbf{0}\right] \\ \mathbf{u} &\sim N\left(0, \sigma^2 \mathbf{V}\right) \\ \mathbf{V} &= diag\left(v_1, v_2, ..., v_N\right) \end{aligned} \tag{1}$$

where $\mathbf{Y}^\star$, $\mathbf{Y}$ and $\mathbf{u}$ are $N \times 1$ vectors. The parameter ρ, also known as the spatial lag, is associated with the non-negative row-standardized exogenous $N \times N$ matrix $\mathbf{W}$. This spatial weight matrix, whose diagonal elements are zero, determines the form of the interdependence across country-pairs. This spatial autoregressive parameter can be seen as a reaction function which relates a country's choice about whether to introduce an eco-label to the existence of an eco-label in spatially close economies. Additional K explanatory variables are included in the $N \times K$ matrix $\mathbf{X}$. To account for potential spatial heterogeneity and outliers, the variance of the error terms, $\mathbf{V}$, is not constant. Following LeSage (1997, 2000), I introduce a set of variance scalars $(v_1, v_2, ..., v_N)$ as unknown parameters to be estimated. This is important, because if a given country follows a different pattern than the majority of the spatial observations, the errors would no longer be normally distributed (i.e. fat-tailed errors associated with a Student-t distribution). The associated parameter estimates would thus be inconsistent if this were not accounted for.

Methods for properly estimating and analyzing equation (1) have recently been the object of a relative large body of research in the spatial econometrics literature. The issue is that the introduction of the spatial lag leads to simultaneity biases as well as additional heteroskedasticity in the error terms. The reduced form of expression (1) highlights this issue:

$$\mathbf{Y}^\star = \left(I - \rho \mathbf{W}\right)^{-1} \left(\mathbf{X}\beta + \mathbf{u}\right) \tag{2}$$

[5] As highlighted by LeSage & Pace (2009), the cross-sectional spatially autocorrelated lag model, which is related to the spatiotemporal model, provides a long term perspective.

The heteroskedasticity as well as the spatial dependence in the error term render standard probit approach inappropriate ($cov\left((I-\rho\mathbf{W})^{-1}\mathbf{u}\right) = \sigma^2 (I-\rho\mathbf{W})^{-1}\mathbf{V}(I-\rho\mathbf{W}')^{-1}$). In fact, the presence of spatial autocorrelation makes the traditional maximum likelihood method less practical. The main reason is that the likelihood function requires to evaluate the joint distribution of the N interdependent outcomes, which is not the product of the N marginal distributions, but involves N-dimensional integration and the determinant of the $N \times N$ matrix $\mathbf{W}$. To see this point more formally, the likelihood function of equation (1) is expressed as follows:

$$\begin{aligned} L\left(\rho,\beta,\sigma^2,\mathbf{V};\mathbf{Y}^\star,\mathbf{W}\right) &= \left(\sigma^2\right)^{-N/2}\left|I_N-\rho\mathbf{W}\right|\left|\mathbf{V}^{-1}\right|\exp\left[-\frac{1}{2\sigma^2}\mathbf{u}'\mathbf{V}^{-1}\mathbf{u}\right] \\ &= \sigma^{-N}\prod_{i=1}^{N}\left(1-\rho\lambda_i\right)\prod_{i=1}^{N}v_i^{-\frac{1}{2}}\exp\left[-\sum_{i=1}^{N}\frac{u_i^2}{2\sigma^2 v_i}\right] \end{aligned} \tag{3}$$

where u_i is the ith element of the error vector $\mathbf{u} = (I_N-\rho\mathbf{W})\mathbf{Y}^\star - \mathbf{X}\beta$. Note that the determinant of the Jacobian $|I-\rho\mathbf{W}|$ is approximated by $\Pi_{i=1}^{N}(1-\rho\lambda_i)$ with λ_i representing the ith eigenvalue of the matrix $\mathbf{W}$.

To avoid the direct calculation of multiple integrals in the likelihood function,which can be analytically intractable, several estimators have been proposed (Fleming, 2004; Franzese & Hays, 2008). McMillen (1992) is the first to suggest an Expectation-Maximization (EM) algorithm. His approach consists of replacing the discrete dependent variable with the expectation of the underlying continuous latent variable and maximizing its likelihood function until convergence is reached. Yet, this method faces several drawbacks (LeSage, 2000). First, the EM algorithm does not provide standard-error for the spatial lag. Second, the method requires an arbitrary parameterization of the heteroskedasticity caused by the introduction of spatial dependence. Third, the approach is highly computation intensive when the number of cross-sections is large. To address the issue of spatial heteroskedasticity, Case (1992) proposes an alternative estimator that groups each cross-section into regions whose errors are assumed to be strictly independent of each other. Instead of expressing the spatial discrete choice model as a maximum likelihood function, Pinkse & Slade (1998), among others, derive the necessary moments conditions and apply a two-step Generalized Method of Moments estimator. Both Case (1992) and Pinkse & Slade (1998) approaches ignore standard cross-section heteroskedasticity making them consistent but not necessarily efficient estimators. More recently, Beron et al. (2003) extend the Recursive-Importance-Sampling (RIS) method to estimate consistently the spatial probit and compute the associated standard-errors necessary for inference. The main disadvantage of this simulation method is its computational burden, which makes it less practical to account for heteroskedasticity in the error term[6]. To address all of these issues, LeSage (2000) extends the Bayesian Markov-Chain-Monte-Carlo (MCMC) method to a spatial discrete choice model by using the Metropolis-Hastings-within-Gibbs sampling approach. The first advantage of the Bayesian strategy is to be able to derive the condition distribution of each parameter, and thus compute different moments of the distribution (e.g. mean, standard-error,...). The second advantage is its flexibility to account for the heteroskedasticity in the error terms. That is why equation (1) will be estimated using the Bayesian MCMC approach.

According to the Bayesian approach, the product of the likelihood function and the prior density, which both depends on certain assumptions, determines the posterior distribution of the parameters that fits the data best[7]. Thus, in order to estimate the set of parameters β, $\mathbf{V}$ and ρ their associated priors ($\pi(\cdot)$) have to be specified independently of each other. First, the explanatory variables are assigned a normal prior, $\pi(\beta) \backsim N(c,\ s)$. Second, in order to account for heteroskedastic variance $\sigma^2 v_i$, the relative variance parameters, $\mathbf{V} = diag(v_1, v_2, ..., v_N)$, are assumed to follow an independent $\chi^2(r)/r$ distribution, which depends on the single parameter r, $\pi(r/v_i) \backsim iid\ \chi^2(r)$, $i = 1, ..., N$. The constant σ is usually set to 1. Third, the spatial lag is assumed to be distributed according to an uniform distribution, $\pi(\rho) \backsim U\left(\lambda_{\min}^{-1}, \lambda_{\max}^{-1}\right)$, where $\lambda_{\min}^{-1}$ and $\lambda_{\max}^{-1}$ represent, respectively, the minimum and maximum eigenvalues of the matrix $\mathbf{W}$. Another alternative is to assumed a beta prior for the spatial autoregressive parameter $\pi(\rho) \backsim \beta(b, b)$ (LeSage & Parent, 2007). Based on these priors, LeSage (2000) extends the work of Albert & Chib (1993) and Geweke (1993) to derive the conditional posterior distributions of the set of parameters:

$$p(\beta|\rho, \mathbf{V}, \mathbf{Y}, \mathbf{Y}^{\star}) \sim \mathrm{N}[\mathbf{C},\ \mathbf{S}] \tag{4}$$

$$\mathbf{C} = \mathbf{S}^{-1}\left[\mathbf{X}'\mathbf{V}^{-1}(I_N - \rho\mathbf{W})\mathbf{Y}^{\star}/\sigma^2 + cs^{-1}\right]$$

$$\mathbf{S} = \mathbf{X}'\mathbf{V}^{-1}\mathbf{X}/\sigma^2 + s^{-1}$$

$$p(v_i|\rho, \beta, \mathbf{V}_{-i}, \mathbf{Y}, \mathbf{Y}^{\star}) \propto \left(u_i^2/\sigma^2 + r\right)/v_i \tag{5}$$

$$p(\rho|\beta, \mathbf{V}, \mathbf{Y}, \mathbf{Y}^{\star}) \propto |I_N - \rho\mathbf{W}|\, e^{-\left(\frac{1}{2}\sigma^2\right)\left(\mathbf{u}'\mathbf{V}^{-1}\mathbf{u}\right)} \tag{6}$$

where $\propto$ means that the expression on the left-hand side is proportional up to a constant to the expression on the right-hand side. $\mathbf{V}_{-i}$ denotes all the elements of the matrix $\mathbf{V}$ beside v_i. Note that expression (6), the prior of the spatial lag, cannot be generated from a standard

[6] In their empirical application, the estimation method proposed by Beron et al. (2003) does not rule out explosive spatial dependence ($\widehat{\rho} > 1$) (see Table 4 p. 292), which can be problematic.

[7] See Holloway et al. (2002), Thomas (2007) or Lesage & Pace (2009) for a more thorougly introduction of bayesian theory extented to the spatial probit.

normal distribution- That is why the Metropolis-Hastings algorithm, which is a standard accept-reject algorithm, has to be used. In the case of the alternative beta prior, an univariate numerical integration is applied to construct the conditional posterior distribution of the spatial autoregressive term and then sample it by *inversion* (LeSage & Pace, 2009).

Finally, the posterior distribution of the latent/auxiliary variable, $\mathbf{Y}^{\star}$, conditional on the parameters is specified as a truncated multivariate normal distribution:

$$\begin{aligned} p\left(\mathbf{Y}^{\star}|\rho,\beta,\mathbf{V},\mathbf{Y}\right) &\sim \mathrm{N}\left[\boldsymbol{\mu},\ \boldsymbol{\Sigma}\right] Ind\left(\mathbf{Y},\mathbf{Y}^{\star}\right) \\ \boldsymbol{\mu} &= \left(I_N-\rho\mathbf{W}\right)^{-1}\mathbf{X}\beta \\ \boldsymbol{\Sigma} &= \left[\left(I_N-\rho\mathbf{W}'\right)\mathbf{V}^{-1}\left(I_N-\rho\mathbf{W}\right)\right]^{-1} \end{aligned} \tag{7}$$

where $Ind\left(\mathbf{Y},\mathbf{Y}^{\star}\right)$ represents an indicator function which truncates from the left by zero if $\mathbf{Y}_i=1$ and from the right by zero if $\mathbf{Y}_i=0$. Note that the marginal distribution of the individual elements of $\mathbf{Y}^{\star}$, $p\left(\mathbf{Y}_i^{\star}|\rho,\beta,\sigma,v_i,\mathbf{Y}_i\right)$, does not correspond to an univariate truncated normal. LeSage's method relies on the Geweke (1991) approach to sample the conditional distribution for $\mathbf{Y}_i^{\star}$ from a truncated multivariate normal distribution subject to independent inequality linear constraints (LeSage & Pace, 2009)[8].

Once the complete conditional distributions of all parameters in the model are specified, the MCMC sampling method can be implemented. While in standard Monte-Carlo simulation, the draws are generated independently based on a specified underlying distribution, in Gibbs sampler, each draw depends on the previous one in such a way that the produced samples display properties identical to those of the joint population. Thus, LeSage (2001) suggests taking iterative random draws from (4), followed by (5) and (6), and then (7). With a sufficient number of draws, the sample statistics can approximate the set of estimates that converges in the limit to the joint posterior distribution of the parameters.

However, the main drawback of LeSage's iterative sampling method is the presence of strong posterior correlation between β, $\mathbf{Y}^{\star}$ and ρ. Although a correlated draws chain provides an unbiased picture of the distribution, the number of draws has to be sufficiently large. That is why, in order to tackle the issue of potential slow mixing in the Markov chain, I follow Holmes & Held (2006) and extends the joint updating of β and $\mathbf{Y}^{\star}$ to a spatial framework by using the product rule to decompose the joint probability of β and $\mathbf{Y}^{\star}$ as follows:

$$p\left(\beta,\mathbf{Y}^{\star}|\rho,\mathbf{V},\mathbf{Y}\right)=p\left(\mathbf{Y}^{\star}|\rho,\mathbf{V},\mathbf{Y}\right)p\left(\beta|\rho,\mathbf{V},\mathbf{Y},\mathbf{Y}^{\star}\right)$$

[8] There are other methods to simulate a truncated multivariate variables subject to inequality linear constraints, including Rodriguez-Yam, Davis & Scharf (2004) efficient approach.

The auxiliary variable is now updated according to its marginal distribution once it has been integrated over β (see equation (4)):

$$\begin{aligned} p\left(\mathbf{Y}^{\star}|\rho,\mathbf{V},\mathbf{Y}\right) &\propto \mathrm{N}\left[\boldsymbol{\mu},\ \boldsymbol{\Omega}\right] Ind\left(\mathbf{Y},\mathbf{Y}^{\star}\right) \\ \boldsymbol{\mu} &= \left(I_N-\rho\mathbf{W}\right)^{-1}\mathbf{X}\beta \\ \boldsymbol{\Omega} &= \left(I_N-\rho\mathbf{W}\right)^{-1}\left[\mathbf{X}s\mathbf{X}'+\mathbf{V}\right]\left(I_N-\rho\mathbf{W}'\right)^{-1} \end{aligned} \tag{8}$$

In other words, the proposed approach consists of sampling $\mathbf{Y}_i^{\star}$ according to its marginal multivariate truncated normal function ($p\left(\mathbf{Y}_i^{\star}|\rho,\mathbf{V},\mathbf{Y}_{-i}^{\star},\mathbf{Y}_i\right)$) and updating β's conditional means ($\mathbf{C}$) after each update to $\mathbf{Y}_i^{\star}$. Once all the individual elements of $\mathbf{Y}^{\star}$ have been sampled, β is generated based on its conditional normal distribution (4). More formally, the new procedure consists of iteratively [9]:

1. updating $\{\beta,\mathbf{Y}^{\star}\}$ jointly according to (8), given ρ and $\mathbf{V}$;
2. updating $\mathbf{V}$ according to (5), given the remaining parameters;
3. updating ρ according to (6), given the remaining parameters.

Thanks to the joint updating approach, the mixing and sampling efficiency in the chain should be improved. In order to compare the performance between the standard iterative sampler and the joint updating sampler, I conduct a small Monte-Carlo simulation study. The latent variable $\mathbf{Y}^{\star}$ is generated according to equation (2) and used to determine the values of $\mathbf{Y}_i$ as follows: $\mathbf{Y}_i = 1$ if $\mathbf{Y}_i^{\star} > 0$ or $\mathbf{Y}_i = 0$ otherwise. The matrix of explanatory variables includes a constant and two standard random normal variables. The coefficient vector is set to the following values: $\beta = (0,1,-1)'$. The spatial weight matrix W is a row-standardized rook-type matrix of order 10 (i.e. the ten nearest neighbors). The spatial autoregressive parameter ρ is set to 0.75. For simplicity, the individual shocks are assumed to follow a standard Gaussian distribution, whose variance is homoskedastic ($\mathbf{u} \sim N\left(0, I_N\right)$). Four different sample sizes are considered: $N = \{250, 500, 750, 1000\}$.

For each of theses designs, 10 samples are generated and estimated according to 6 different samplers:

1. iterative update with Geweke approach to simulate the latent variable and Metropolis-Hastings algorithm to draw the spatial lag.

[9] The algorithm is written in Matlab and available upon request.

2. iterative update with Geweke approach to simulate the latent variable and numerical integration to draw the spatial lag.

3. iterative update with Rodriguez-Yam, Davis & Scharf approach to simulate the latent variable and Metropolis-Hastings algorithm to draw the spatial lag.

4. iterative update with Rodriguez-Yam, Davis & Scharf approach to simulate the latent variable and Metropolis-Hastings to draw the spatial lag.

5. joint update with Metropolis-Hastings algorithm to draw the spatial lag.

6. joint update with numerical integration to draw the spatial lag.

To my knowledge, this the first time that the approach suggested by Rodriguez-Yam, Davis & Scharf (2004) and the joint update have been applied to estimate a spatial probit. In order to measure efficiency, I compute, for each chain, the CPU computation time in seconds, the parameters' average Euclidean update distance between each iteration as well as the Raftery-Lewis (1992, 1995) convergence statistic . A large value of Euclidean distance means good mixing while a high total number of draws necessary to ensure an i.i.d chain implies high autocorrelation in the chain and slow convergence.

Table 2 presents the results averaged over the four parameters (β and ρ) and the 10 runs. First, the method proposed by Rodriguez-Yam et al. (2004) is more efficient than Geweke (1993) with higher mixing and faster convergence. Second, applying numerical integration to draw the spatial lag improves also the mixing and usually reduces autocorrelation in the chain. Third, although it is relatively more time consuming when the sample size is large, the joint updating sampler yields a larger average distance jumped between iterations and usually relies in smaller total draws. In fact, once the performances are standardized by their respective computation time, the joint sampling algorithm relies on a 45% smaller total number of draws to ensure convergence[10]. In addition, in comparison to Geweke method, the joint sampler yields 15 to 50% more mixing in the chain. Interestingly, Rodriguez-Yam et al.'s approach can lead to the same level of mixing than the joint updating method when the number of cross-sections is particularly large. Overall, these findings suggest that the spatial probit model should be estimated by the joint update algorithm, especially when the sample size is relatively small (as it is the case in this study).

[10] Appendix 8.A reports the relative performance of the iterative samplers with respect to the joint updating sampler.

Table 2: Algorithms Performance

	Iterative Update with Geweke & Metropolis-Hastings			Iterative Update with Rodriguez-Yam et al. & Metropolis-Hastings			Joint Update with Metropolis-Hastings		
Observations	CPU Time	Total Draws	Param. Distance	CPU Time	Total Draws	Param. Distance	CPU Time	Total Draws	Param. Distance
250	51	5268	0.145	37	4032	0.149	45	4164	0.192
500	176	5130	0.103	135	4209	0.106	170	3844	0.137
750	390	5172	0.083	313	4118	0.086	416	3947	0.111
1000	725	5160	0.072	585	3863	0.075	841	3816	0.096

	Iterative Update with Geweke & Numerical Integration			Iterative Update with Rodriguez-Yam et al. & Numerical Integration			Joint Update with Numerical Integration		
Observations	CPU Time	Total Draws	Param. Distance	CPU Time	Total Draws	Param. Distance	CPU Time	Total Draws	Param. Distance
250	55	5580	0.158	41	4065	0.163	49	3911	0.204
500	194	5164	0.112	153	3947	0.116	187	3916	0.145
750	444	5251	0.092	368	3813	0.095	469	3811	0.118
1000	839	5035	0.078	715	3770	0.081	956	3905	0.101

Once the model has been estimated, it is crucial to be able to interpret the coefficients (first and second moments of the conditional distribution). Yet, just like in standard discrete choice models, parameter estimates from a spatial probit cannot be interpreted directly. They must be transformed to yield estimates of the marginal effects, i.e. a change in the predicted probability associated with changes in the explanatory variables. However, unlike classical approaches, models including a spatial lag of the dependent variables have to be interpreted in a special way (Beron & Vijverberg, 2004). This comes from the fact that a change in a single country associated with a given explanatory variable will lead to a direct impact on the country itself, but can potentially affect all other countries indirectly. In fact, spatial probit model allows for complex feedback loops that might take place when a shock in country i affects countries j and k to finally change back country i. The derivative of Y_i with respect to a variable r in country j, $(j = 1, ..., i, ...N)$ takes the following form:

$$\widehat{\Xi}_{ijr} \equiv \frac{\partial E\left[Y_i \middle| X_{jr}\right]}{\partial X_{jr}} = \phi\left(\left[\left(I_N - \widehat{\rho}\mathbf{W}\right)^{-1} X\widehat{\beta}\right]_i / \widehat{s}_i\right) \left[\left(I_N - \widehat{\rho}\mathbf{W}\right)^{-1}\right]_{ij} \widehat{\beta}_r / \widehat{s}_i$$

where ϕ is the density function of a standard normal distribution and $\widehat{s}_i = \widehat{\sigma}^2 \sum_i \widehat{\omega}_{ij}^2$ with ω_{ij} being the ij^{th} elements of the matrix $(I - \rho\mathbf{W})^{-1}\,\mathbf{u}$.

Since it might be difficult to keep track of the $N^2 \cdot K$ spatial effect estimates, when the spatial weight matrix size and the number of explanatory variables are large, LeSage & Pace (2009) suggest some useful summary measures of these effects for each explanatory variable r:

- Average Total Effect: $\widehat{\Xi}_r^T = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N}\widehat{\Xi}_{ijr}$.
- Average Direct Effect: $\widehat{\Xi}_r^D = \frac{1}{N}\sum_{i=1}^{N}\widehat{\Xi}_{iir}$.
- Average Indirect Effect: $\widehat{\Xi}_r^I = \widehat{\Xi}_r^T - \widehat{\Xi}_r^D$.

Going back to the eco-label analysis, these impacts could be interpreted in the following way. The direct effect indicates how a rise in an explanatory variable across the sample of countries would affect the expected probability of the (average) country to adopt an eco-label scheme. The indirect effect measures how a shift in this explanatory variable would affect the (average) neighboring country's eco-label program adoption decision. Obviously, the size of these types of feedback will depend on the position and degree of connectivity of each country with each other (spatial weight matrix W), the strength of spatial dependence (spatial lag ρ) and the importance of the explanatory variables (parameters β).

4 Determinants of Eco-Label Adoption

As mentioned previously, the analysis of the effect of eco-labels on trade flows suffers from fundamental data deficiencies (OECD, 2004). Because import and export statistics apply different universal codes for tracking trade flows of eco-labelled and non-eco-labelled products, there is no information available on international trade in eco-labelled products. That is why this paper put the focus on governmental or quasi-governmental multi-sector eco-label programs. Unlike one single product category label (e.g. canned tuna caught in a dolphin safe way) or private eco-label (e.g. certified wood), the type of label considered here covers a wide range of different manufactured products categories (e.g. Germany's Blue Angel). Data on the adoption of a type I eco-label is taken from the Global Eco-labelling Network as well as the New Zealand's Ministry of Economic Development and the website ecolabelling.org. Appendix 8.B reports the countries which have adopted a multi-sector eco-label before 2009[11].

[11] Due to missing data, Liechtenstein, Malta, Singapore and Taiwan are not considered, although they have an eco-label implemented. In addition, Costa Rica, South Africa, Turkey and Zimbabwe have introduced a tourism eco-label. But since this type of eco-labelling focuses on non-traded goods, they are deliberately omitted.

Several authors have defined the potential determinants that could explain why a country and producers would adopt an eco-label (Grolleau & El Harbi, 2008). Among them, Basu et al. (2004) determine analytically and empirically the economic, trade and environmental variables under which governments and agricultural firms that apply green production methods are favorably selected in the set of countries that adopt an eco-label program. They also investigate the strategic interactions that prevail between trading partners in their decision to adopt the eco-label. Based on their theoretical framework, which can be extended to manufacturing industries, Figure 1 depicts the main incentives behind the government's decision to introduce an eco-label. The perceived gains resulting from the adoption of an eco-label are related to (1) the stage of development of the adopting country, (2) the fixed cost of the eco-labelling scheme, (3) the relative production cost advantage of the country in producing the type of products covered by the eco-label program and (4) the strategic interactions between trade competitors. The table in Appendix 8.E presents the different factors and proxies as well as their sources considered in this paper.

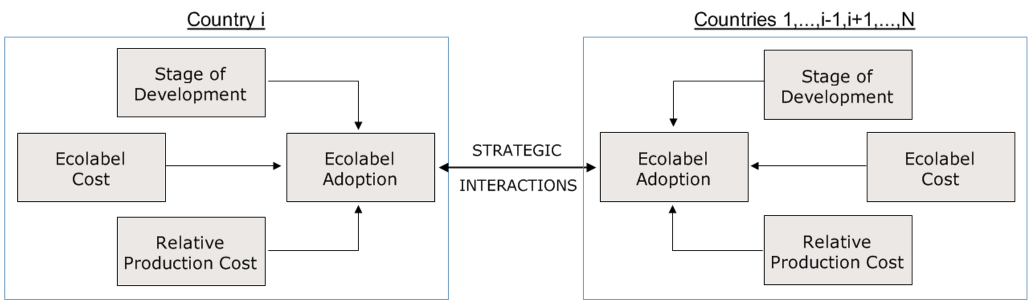


Figure 1: Ecolabel Determinants

4.1 Economy's Stage of Development

The decision to adopt an eco-label is mainly determined by the stage of development of the economy. This is partially confirmed by Figure 2 which highlights the fact that most high income countries were among the first to introduce an eco-labelling scheme[12]. In particular, several governments decided to introduce an eco-label during the 1980s and early 1990s, coinciding with the trend of market governance and self-regulation in environmental policy instrument (away from command-and-control measures). In the recent years, the need to address the issues related to global warming has lead to a renewed interest in eco-labelling scheme.

[12] The peak in 1992 and 2004 correspond to the introduction and extension of the European eco-label program, EU(15) and EU(25), respectively. Note that several european countries (e.g. Germany (Blue Angel), Netherlands (Stichting Mileukeur), ...) introduced an eco-label program before the UE Flower ecolabel. For those cases, only the first eco-label scheme introduced is considered (see Appendix 8.B).

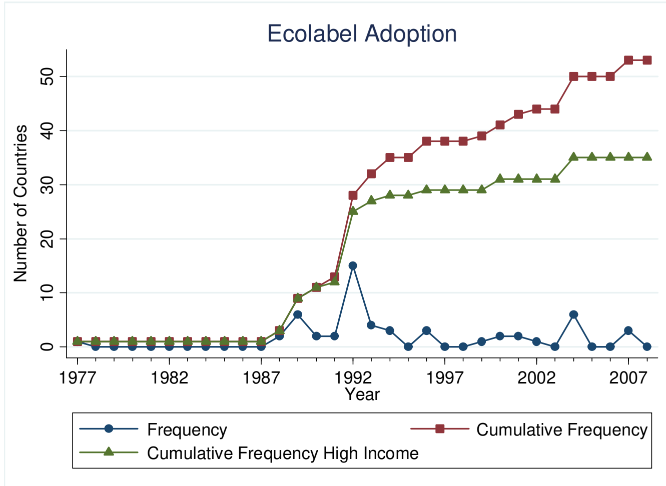


Figure 2: Eco-label Adoption Evolution over Time

According to the environmental Kuznet curve representation, as the economy becomes richer, individuals are more aware of environmental issues and ask for stringer regulation in order to reduce and reverse the environmental pollution trend resulting from industrialization. Countries that face more social problems (e.g. high unemployment rate, child mortality rate, wage inequality, ...), all things being equal, are more likely to assign a low degree of concern for environmental issues, reducing the probability of introducing an eco-labelling scheme.

More generally, based on classic economic theory, market-based instruments like eco-labelling scheme are more likely to be implemented by efficient governments than command-and-control standards. Moreover, if the threat of direct environmental policy regulation on the environmental quality of the product is high, producers might support more strongly the introduction of an eco-labelling scheme. All other things being equal, the probability to introduce an eco-label program will decrease as the economy is characterized by high inefficiency and corruption preventing private sector from any voluntary environmental initiatives. Somehow related to the issue of corruption, democratic governments with high political freedom can support more easily environmental quality improvement measures through voters' preferences (Magnani, 2000) and thus increase the odds of introducing an eco-label program.

4.2 Cost of Eco-label

Several reasons can lead a firm to opt to be a member of an eco-label program (e.g. improved corporate reputation, risks mitigation and management, competitive advantage, access to new markets, cost reductions in the long run, ...). Ultimately, the producers's decision is based on comparing two options (Sedjo et al., 2002):

- the extent to which the eco-label would increase the production costs (i.e. investment costs to comply with the eco-label's standards (indirect costs) and administrative costs associated with the eco-labelling procedure (direct costs));
- the extent to which consumers are willing to pay a price premium for eco-labelled products (i.e. predictability of the producers' future revenues).

Firms in large domestic markets will be able to dampen the fixed cost to be paid to be certified by a third party through economies of scale and improved learning curves. These elements play a key role in the development of differentiated goods (Bruce & Laroiya, 2007). As highlighted by Nadai (1999), the firms' eco-label adoption strategy is partially determined by the degree of heterogeneity between the sets of products sold. In addition, before the market phase, the government might face the opposition of some firms in the industry during the negotiation of the eco-label's criteria. These firms might want to try to block the agreement on the criteria or, if these criteria are nonetheless adopted by the authority, they can deliberately avoid the use of a label on their products.

Consumer sensitivity to the environment, which is related to the country's stage of development, is also essential for eco-labelling programs to be effective. In fact, the proportion of environmentally concerned consumers in the economy and their willingness to pay for public good characteristics increase the probability to adopt an eco-label. Results from a number of studies (Teisl et al., 1999; Sammer et al., 2006) suggest that two of the major reasons why consumers choose eco-labelled products are consideration for the environment and/or for their own health. Several demographic and economic characteristics play a role in determining eco-friendly behaviors. For instance, younger and more educated individual usually display a lower information processing cost and thus are assumed to be more proactive in terms of environmental quality requests. In particular, the level of the green premium price is stimulated if consumers are already environmentally conscious and able to express their preferences through their environmentally friendly consumption choices.

In addition, countries characterized by larger population densities are usually in need of a better environmental quality, because the lives of more people are affected by pollution. Yet, the relationship between attitudes and behaviors with respect to the environment is not simple and straightforward. The reason is that consumers are often dealing with mixed motives[13].

4.3 Relative Production Cost Advantage

In order to be awarded an eco-label on their products, firms have to invest more in environmentally sound technologies. This suggests that the criteria of the eco-labelling scheme will implicitly orient firms' R&D. In fact, eco-label regulators expect that producers will achieve innovation during the market phase in order to respect the criteria. Therefore, the diffusion of eco-organizational innovations can ultimately improves the relative production cost advantage of an economy in producing different products (Porter & Van der Linde, 1995). Innovative industries will then be more inclined to support policy instruments that promote innovation. One can expect this mechanism to be even stronger, if producers are already familiar with environmental innovations (e.g. standard-setting, certification and accreditation procedures), reducing the cost of the negotiation and market phases of the eco-label program.

However, the introduction of an eco-labelling scheme might also lead to innovation distortions. In particular, during the eco-label criteria negotiation, producers may try to ensure that the standards would rely on the current technology they possess, ensuring the lowest environmental innovation costs as possible. Once the eco-labelling scheme is in place, producers might have no additional incentive to innovate beyond the eco-label's standards, even when they enjoy a larger profit margin in the market. Distortion might be further exacerbated by exporting firms desiring to comply with the WTO's rule of non-product related process and production methods and thus dissuading them from investing in greener technologies.

[13] Several explanations have been provided, such as the "warm glow effect" (i.e. increased utility from the act of giving rather than receiving) or the "Veblen effect" (increase utility associated with the statut value given by the consumption) *versus* an excessive premium price charged or a lack of trust in the eco-labelled product (Peattie, 2001; Pedersen & Neergaard, 2006).

4.4 Strategic Interactions with Trade Competitors

The emergence of environmental demands in export markets is more likely to be important in open economies. Since environmental attributes are unobservable, an eco-labelling scheme can serve as a screening mechanism or a signalling device. That is one of the reason why developing countries are concerned with the possible manipulation of eco-label standards as a non-tariff barrier in disguise. From this point of view, the adoption of an eco-label scheme can be seen as a substitute to a tariff system. As far as I know, this substitutive relationship has yet to be investigated empirically.

If an eco-labelling scheme is considered as a potential strategic environmental policy, then the decision to introduce an eco-label program can be seen as the outcome of a reaction function of the other countries' behavior. More specifically, the interdependence in the eco-label adoption relies on two hypothesis:

Hypothesis 1: *As a leader (follower), a country's incentive to adopt an eco-label is negatively (positively) affected by the absence (existence and future existence) of eco-label programs in other countries.*

Hypothesis 2: *This eco-label adoption interdependence increases with high economic relationship intensity and decreases with large trade cost.*

To account for the existence of a peer effect a spatial lag term (ρ) is thus included in the model specification. In order to avoid any endogeneity issue in the estimation process, the interdependence of the spatial autoregressive parameter is based on a geographical distance weighting scheme ($\mathbf{W}$), which is by definition strictly exogenous. The benchmark spatial weight matrix is based on a negative exponential distance measure:

$$w_{ij} = \begin{cases} \exp\left(\frac{-distance_{ij}}{500}\right) & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases}$$

where $distance_{ij}$ is the bilateral geographical distance between the capital of country i and j. The advantage of this spatial scheme is to give a positive weight to countries which are close to each other (within a region) and almost zero weight to nations that are geographically remote from each other. Note that the spatial weight is row-standardized so that the sum of each row is equal to one.

5 Empirical Results

The selection of the explanatory variables is mainly dictated by their availability in order to maximize the number of countries in the sample ($N = 141$). The table in appendix 8.D lists the countries considered in this paper. In order to reduce multicollinearity issues, I deliberately restrict the number of explanatory variables. Multicollinearity leads to technical issues and convergence problems. The tables in appendix 8.F and G report the descriptive statistics of the variables, the Moran's spatial autocorrelation statistic as well as the correlation matrix. As suspected, the eco-label dummy variable displays significant positive spatial autocorrelation. The same is true for the remaining variables considered in this study. This definitively calls for a spatial framework.

Before implementing the joint updating MCMC algorithm, several decisions have to be made. These include the values for the priors' parameters, the number of total iterations, the number of initial burn-in to be discarded and the spacing between iterations to be retained for the inference[14]. In fact, it is important to determine whether the sampling chain has converged to a stationarity distribution. So the question is what is the number of runs until the Markov chain approaches stationarity. According to Raftery and Lewis (1992, 1995) diagnostic statistics and autocorrelation measures, the estimation relies on a Monte Carlo chain which is based on at least $15,000$ draws with $1,000$ burn in draws and a thinning factor of at least 5. The main reason to ignore $1,000$ draws is to make sure that there is no systematic information left in the random numbers generation process for the remaining draws. In addition, only every 5th draw is saved for inference in order to reduce autocorrelation and avoid unjustified higher standard deviation in the parameters. If the chain for each parameter were to display high autocorrelation, further draws from the chain should be skipped in order to get proper inference on the standard deviation.

For each spatial specification, the average coefficients' posterior and its associated standard errors are reported in the first column. The estimated parameters' t-statistics are not computed. The main reason is that normalization by standard errors does no longer leads to a Student distribution, because the simulated draws are themselves approximation to Student distributions (Holloway et al., 2002)[15]. In addition, as suggested by LeSage & Pace (2009), the second to fourth columns report the average marginal direct, indirect and total effect, respectively. But first, I estimate the model assuming there is no spatial dependence in the eco-label decision in a homoskedastic framework. Table 3 reports the main results.

[14] Unless specified otherwise, the priors' settings are set as follows: $\pi(\beta) \backsim N\left(0,\ I_N \cdot 1e^{12}\right)$, $\pi(\rho) \backsim ß(1.01, 1.01)$, and $\pi(4/v_i) \backsim iid\ \chi^2(4)$, $i = 1, ..., N$.

[15] Here, a parameter is significant at the 5 percent significance level, if the quantiles at the 2.5 and 97.5 percent have the same sign, i.e. zero does not belong to the 95% interval.

The traditional probit estimator performs relatively poorly. Most variables are not significant at the conventional level, except the number of international environmental treaties adopted, the share of high technology exports and the number of ISO14001 certificates. The presence of large standard errors might be due to the strong assumption of homosedasticity in the error term and a potential variable omission when spatial dependence is not accounted for. These issues are addressed by estimating an heteroskedastic spatial probit model. According to different convergence checks instruments, the different Monte Carlo chains have reached stationarity[16]. In particular, the dependence statistic I, which reports the ratio of the total number of draws required to achieve a 5 percent test accuracy and the minimum number of draws needed to ensure an identically and independently distributed draws, is lower than 5 ($I = 1.93$). Therefore additional draws are not required and proper inference can thus be performed.

Once interdependence in the eco-label adoption is taken into account, the results improve significantly. In fact, although not necessary significant at the conventional level, most parameters display the expected sign. In particular, countries which have reached a high stage of development are more likely to adopt an eco-label. This is confirmed by the fact that GDP affects positively the environmental label decision. As the economy growths, the government has the incentive and the means to introduce an eco-labelling scheme. Interestingly, the pollution pressure capture by emissions of SO2 decreases the probability of implementing an eco-label scheme. This counterintuitve result might be due to three reasons. First, several high income countries are large SO2 emitters despite possessing an eco-labelling scheme (e.g. Switzerland or Sweden) and low income countries without eco-label generate even higher levels of SO2 emissions (e.g. Mali or Nigeria). Second, most environmental labellings cover products in industries characterized with relatively low SO2 emissions (e.g. footwear or textile)[17]. Third, since the SO2 emissions' impact on the environmental and health is relatively local, the need of direct regulation can be higher and the government might prefer command-and-control measures instead of self-enforcement instruments. This finding can be linked to Mattoo & Singh (1994) and Swallow and Sedjo (2000)'s theoretical results, who show that in some circumstances the labelling scheme could lead to an adverse effect on the environment by stimulating the production of unlabeled products through a substitution effect when the environmentally friendly production exceeds the demand and the relative price of labelled goods increases. Going back to the estimation results, the existence of scale effect,

[16] In order to check the convergence of the MCMC samplers, autocorrelation, Raftery-Lewis and Geweke diagnostics have been performed. To save space, they are not reported here but are available upon request.

[17] The non-ferrous metals, petroleum, non-metallic mineral and chemical products are associated with large level of SO2 emissions (see Emission Data Base for Global Atmospheric Research).

Table 3: Estimation Results

	Standard Probit		Spatial Probit with Exponential Distance			
Variable	Coefficient	Marg. Effect	Coefficient	Direct Effect	Indirect Effect	Total Effect
Constant	-0.04305		2.662			
	[4.104]		[7.29]			
Real GDP per Capita	0.0986	0.02516	0.1953***	0.007481***	0.001391**	0.008872***
	[0.06036]	[0.01412]	[0.08749]	[0.003256]	[0.0009093]	[0.003949]
So2	-0.02581	-0.006586	-0.08733*	-0.003314*	-0.0006521*	-0.003966*
	[0.02647]	[0.007974]	[0.05499]	[0.001983]	[0.0005536]	[0.002464]
Political & Civil Rights	-0.1574	-0.04015	-0.2164	-0.008878	-0.001425	-0.0103
	[0.2192]	[0.04827]	[0.3359]	[0.01362]	[0.002652]	[0.01603]
Population Below 45	-0.08726	-0.02226	-0.1698	-0.006498	-0.001194	-0.007691
	[0.0809]	[0.01505]	[0.1232]	[0.004814]	[0.001109]	[0.005754]
Environmental Treaties	0.06722***	0.01715***	0.1109***	0.004248***	0.0007562**	0.005004***
	[0.02386]	[0.009666]	[0.03929]	[0.001384]	[0.000375]	[0.001597]
Manufacture Value Added	0.06518	0.01663	0.1942***	0.007387***	0.001439**	0.008826***
	[0.0443]	[0.01454]	[0.07449]	[0.00252]	[0.0009026]	[0.003249]
High Technology Exports	0.04323*	0.01103*	0.09391***	0.003628***	0.00069**	0.004318***
	[0.02297]	[0.008284]	[0.04012]	[0.001536]	[0.0004538]	[0.001897]
ISO14001	0.2888***	0.07369***	0.399***	0.01558***	0.002712**	0.0183***
	[0.09417]	[0.02957]	[0.1384]	[0.005775]	[0.001235]	[0.006479]
Manufacture Tariff	-0.1038	-0.02648	-0.08972	-0.003516	-0.0005318	-0.004048
	[0.07548]	[0.02185]	[0.1046]	[0.00414]	[0.0007762]	[0.004811]
Spatial lag			0.1555**			
			[0.06]			
Observations	141		141			
Total Draws / Omitted Draws	-		15000 /1000			
Thinning Factor	-		5			
I-statistic	-		1.927			
Log-likelihood	-17.568		-18.712			
Pseudo R^2	0.804		0.792			

Note: The mean of the posterior distribution is reported as coefficient while the standard deviation is reported in the brackets. *** significant at 1%, ** significant at 5%, * significant at 10%.

captured by the manufacture value added share, increases the probability. In other words, if the costs associated with the eco-label procedure can be compensated by economies of scales, the probability to introduce an eco-label is positively significant. The same does not hold for the presence of a green price premium proxied by the population share below 45 years old. This probably comes from the fact that it is an imperfect proxy, since most high income countries with an eco-label in place have fewer young adult people relative to developing countries. Results show that economies displaying a relative production cost advantage through previous environmental preferences experience, innovation and a high share in high-technology exports are more inclined towards adopting a voluntary environmental program. This result is in line with Grolleau & El Harbi (2008), who finds that economies characterized with higher technological innovation capacities use the eco-labelling scheme as a tool to enhance and reinforce their innovation potential. In fact, there is some kind of "path dependency" that shapes the diffusion of environment friendly organizational innovations through ISO14001 certificates leading ultimately and more easily to the adoption of an eco-label program. Although there seems to be a substitutive relationship between the adoption of an eco-label and the average manufacturing tariff, it is not statistically significant. Finally, nations which are closer to each other in economic and geographical terms display a higher probability of adopting an eco-label program. Thus, hypothesis 1 and 2 related to the interdependence nature of the eco-label decision are supported.

In comparison with the classical probit model, there are major differences in terms of average coefficients and marginal effects, the spatial direct marginal effects being theoretically equivalent to the standard marginal effects. Beside the fact that the number of explanatory variables significantly different from zero is higher in the spatial probit estimation, accounting for spatial dependence usually yields higher average estimates but lower average direct marginal effects in absolute value. This is mainly due to a larger average posterior of the constant in the spatial probit and a rate of decay relatively faster of the spatial dependence. This also explains why the indirect effects, which can be interpreted as the probabilistic impact of a rise in the neighborhood of a given explanatory variable on the eco-label decision, are always smaller than the direct effects. The largest average total effects are associated with a high number of ISO14001 certificates, a strong level of economic development and potentially large scale effects.

In order to further investigate the impact of interdependence, it can be of interest to compare the predictive power of the spatial probit model with respect to the standard probit model, because the McFadden pseudo R^2 can be misleading. As in most empirical studies considering a probit framework, I assume that the model is able to predict the eco-label adoption (i.e. $Y_i = 1$) when the predicted probability is equal to or larger than 50 percent. In the benchmark sample, the proportion of countries having introduced an eco-label program is about 33.33 percent. The fact that the sample is *unbalanced* makes any prediction more difficult. Yet, evidence suggests that accounting for spatial dependence definitively increases the explanatory power of the model. The standard probit model predicts 90.78 percent of the cases correctly, while its spatial extension displays a higher predictive power with 94.33 percent. Among the eco-label adopters, 85.11 percent are also predicted correctly by the spatial model and only 78.72 percent by the simple probit model. Once again, this highlights the importance of accounting for interdependence in the eco-label adoption. Interestingly, according to the spatial probit model, some less developed countries should not have implemented an eco-label (e.g. Indonesia, Russia, Ukraine,...), while Chile should have adopted one. Actually Chile was among the first to introduce an eco-label in the forestry industry (CERTFOR). Moreover, at the end of 2009 the Chilean government proposed a bill that require producers, distributors and importers to label goods with information on the environmental impacts posed by their products.

Table 4: Model's Predictive Power

	Standard Probit Model		Spatial Probit Model		
	Predicted Eco-label	Predicted No Eco-label	Predicted Eco-label	Predicted No Eco-label	Total
Observed Eco–label	37	10	40	7	47
Observed No Eco-label	3	91	1	93	94
Total	40	101	41	100	141

6 Robustness Check

In order to investigate the robustness of the previous findings, several sensitivity analysis are performed. First, I check if the estimates are sensitive to a modification of the Markov Chain Monte Carlo settings. Second, different expressions of the spatial weight matrix are considered. Last but not least, I estimate the spatial error and Durbin version of the benchmark model in order to account for some potential omission variables. Overall, the conclusions based on the benchmark model prevail and confirm the existence of spatial dependence in the eco-label decision.

6.1 MCMC's setting

Several Monte Carlo studies showed that the estimation of non-linear probability models can be sensitive to the degree of heteroskedasticity of the disturbances. The benchmark results were obtained under the following variance's prior $\pi\left(4/v_i\right) \backsim iid\ \chi^2\left(4\right)$. Therefore, in order to check the robustness of the main results, I re-estimate the model by setting a different value for the hyperparameter r, either assuming the prior distribution is more asymmetric and skewed ($r = 3$) or the prior distribution is symmetric ($r = 10$). I also estimate the model under the assumption of no heteroskedasticity in the residuals' variance, i.e. $v_i = 1$, $i = 1, ..., N$.

To save space, I only report in Table 5 the results of the heteroskedastic and asymmetric versus the symmetric and homoskedastic case. Overall, the results remain qualitatively similar. Higher or lower skewness parameter of the variance χ^2 distribution does not alter the findings. The decision to introduce an ecological label is still spatially dependent. However when $k = 3$, the results are more sensitive, because the algorithm breaks down when a smaller value for the hyperparameter r is considered ($r = 2$). In any case, most of the marginal estimates remain in the same range as in the benchmark, suggesting that the results are robust to an alteration of the MCMC's algorithm. This might be surprising, since a simple *t-test* rejects the hypothesis that each average estimated individual variance term ($\widehat{v}_i$) is equal to 1. Although not reported, but available upon request, the results are also robust to a change in the initial value of the spatial autoregressive parameter and the covariance matrix of the prior distribution of β.

6.2 Spatial Weight Matrices

In order to shed light on the relative intensity of interdependence in the eco-label decision, I re-estimate the model using four alternative spatial weighting matrix $\mathbf{W}$. First, I consider the simple inverse bilateral distance which allocates a positive weight to all countries, including very remote ones. In fact, strategic dependence can be effective, even beyond its own geographical region. The corresponding spatial weight matrix is defined as follows:

$$w_{ij} = \begin{cases} \frac{1}{distance_{ij}} & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases}$$

Table 5: MCMC Robustness Check Results

	Spatial Probit with Exponential Distance Heteroskedastic & Asymmetric Case ($k=3$)				Spatial Probit with Exponential Distance Symmetric & Homoskedastic Case			
Variable	Coefficient	Direct Effect	Indirect Effect	Total Effect	Coefficient	Direct Effect	Indirect Effect	Total Effect
Constant	3.59				1.948			
	[9.174]				[4.858]			
Real GDP per Capita	0.1979**	0.006741**	0.001342**	0.008083**	0.1499**	0.007415**	0.001169**	0.008583**
	[0.1044]	[0.003645]	[0.001029]	[0.004424]	[0.06925]	[0.00326]	[0.0007657]	[0.003905]
So2	-0.1164**	-0.003806**	-0.0008191*	-0.004625**	-0.05888**	-0.002904**	-0.0004629*	-0.003367**
	[0.0749]	[0.002167]	[0.0007178]	[0.002746]	[0.03116]	[0.001451]	[0.0003246]	[0.001729]
Political & Civil Rights	-0.2188	-0.008124	-0.001217	-0.009341	-0.2666	-0.01345	-0.001977	-0.01542
	[0.3801]	[0.0137]	[0.00302]	[0.01637]	[0.2345]	[0.01193]	[0.001974]	[0.0137]
Population Below 45	-0.174	-0.005906	-0.001152	-0.007057	-0.1444	-0.007175	-0.001117	-0.008293
	[0.1612]	[0.005623]	[0.001406]	[0.006821]	[0.09934]	[0.004918]	[0.0009513]	[0.005758]
Environmental Treaties	0.1305***	0.004367***	0.0008221**	0.00519***	0.08505***	0.004192***	0.0006308**	0.004823***
	[0.05175]	[0.001601]	[0.0004293]	[0.001848]	[0.02768]	[0.001077]	[0.0002676]	[0.001236]
Manufacture Value Added	0.2337***	0.007713***	0.001636**	0.009348***	0.126***	0.006219***	0.0009995**	0.007219***
	[0.09843]	[0.002785]	[0.001159]	[0.00363]	[0.05099]	[0.002229]	[0.0006003]	[0.002732]
High Technology Exports	0.1112***	0.003741***	0.0007623**	0.004504***	0.07256***	0.003571***	0.0005557**	0.004126***
	[0.05148]	[0.001652]	[0.0005263]	[0.002043]	[0.0307]	[0.001302]	[0.0003118]	[0.001548]
ISO14001	0.4482***	0.01543***	0.002744**	0.01817***	0.3866***	0.01913***	0.002837**	0.02196***
	[0.1735]	[0.006882]	[0.001403]	[0.007704]	[0.1056]	[0.003907]	[0.001006]	[0.004278]
Manufacture Tariff	-0.1139	-0.003923	-0.0006166	-0.00454	-0.08884	-0.004435	-0.0006002	-0.005035
	[0.1248]	[0.004504]	[0.0009358]	[0.005216]	[0.0705]	[0.003524]	[0.0005413]	[0.003982]
Spatial lag	0.1653**				0.1327**			
	[0.07262]				[0.04449]			
Observations	141				141			
Total Draws / Omitted Draws	15000 /1000				15000 /1000			
Thinning Factor	4				5			
I-statistic	2.403				1.786			
Log-likelihood	-24.998				-14.188			
Pseudo R^2	0.721				0.842			

Note: The mean of the posterior distribution is reported as coefficient while the standard deviation is reported in the brackets.
*** significant at 1%, ** significant at 5%, * significant at 10%.

A second spatial weight matrix is constructed based on the minimum political distance database built by Gleditsch & Ward (2001). The main reason to consider this measure is that the type of eco-labels considered in this study are in most cases the result of a political decision. In addition, empirical evidence suggests that political interests are a major determinant in the attitude towards preventing environmental damage. This political distance measure is based on the minimum geographical distances for all governments within 950 kilometers of each other in the year 2000. Note that the structure of this political distance measure is not simply geographical. For instance, according to Gleditsch & Ward, there is no political influence between Canada and USA:

$$w_{ij} = \begin{cases} \frac{1}{political\ distance_{ij}} & \text{if } i \neq j \text{ and } distance_{ij} \leq 950 \text{ km} \\ 0 & \text{if } i = j \end{cases}$$

Third, I consider a spatial weight matrix based on the average bilateral trade between 1995-2000 to explicitly account for trade intensity between countries. Accordingly, strategic dependence should be higher with countries characterized by high trade intensity between them:

$$w_{ij} = \begin{cases} trade_{ij} & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases}$$

However, trade intensity might be a measure of strategic interdependence too broad, because despite important trade flows, countries can in reality share small strategic interdependence if each one is specialized in different type of products. That is why, following Cao & Prakash (2009), the last spatial weight matrix is constructed based on countries' export structural equivalence. The export profile corresponds to the correlation between manufacturing exports of country i and j at both bilateral and sector levels to the remaining economic partners[18]. A $structural\ equivalence_{ij}$ close to 1 implies that country i and j export the same type of goods to the same other partner countries. In other words, economy i and j are competitors since they export similar products to the same foreign markets. Therefore, one can expect strategic interactions to be stronger between countries in competition:

$$w_{ij} = \begin{cases} structural\ equivalence_{ij} & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases}$$

[18] Based on the United Nations' Standard International Trade Classification, four manufacturing sectors are considered: (1) chemical and related products; (2) manufactured goods; (3) machinery and transport equipment: (4) miscellaneous manufactured articles.

Table 6: Spatial Weight Robustness Check Results

	Spatial Probit with Inverse Distance				Spatial Probit with Inverse Political Distance			
Variable	Coefficient	Direct Effect	Indirect Effect	Total Effect	Coefficient	Direct Effect	Indirect Effect	Total Effect
Constant	12.81				2.172			
	[12.51]				[5.281]			
Real GDP per Capita	0.3489***	0.007057***	0.02171***	0.02877***	0.1223**	0.005579**	0.001184**	0.006763**
	[0.1325]	[0.002789]	[0.02273]	[0.02362]	[0.06657]	[0.002942]	[0.0007068]	[0.003475]
So2	-0.2093***	-0.004241***	-0.01534***	-0.01958***	-0.05814*	-0.002656*	-0.0006474*	-0.003304*
	[0.09612]	[0.002035]	[0.02025]	[0.02143]	[0.03217]	[0.001409]	[0.0005022]	[0.001847]
Political & Civil Rights	-0.4915	-0.009545	-0.01395	-0.02349	-0.2702	-0.01262	-0.002725	-0.01535
	[0.662]	[0.01342]	[0.04633]	[0.05601]	[0.2264]	[0.01079]	[0.002597]	[0.01308]
Population Below 45	-0.431**	-0.00846**	-0.02768**	-0.03614**	-0.1476	-0.006838	-0.001517	-0.008354
	[0.2461]	[0.00455]	[0.03864]	[0.04094]	[0.1005]	[0.004682]	[0.001243]	[0.005741]
Environmental Treaties	0.1794***	0.00363***	0.01033***	0.01396***	0.09075***	0.004162***	0.0009401***	0.005102***
	[0.07151]	[0.001477]	[0.008961]	[0.009255]	[0.02702]	[0.001079]	[0.0004175]	[0.001328]
Manufacture Value Added	0.2997***	0.006173***	0.02007***	0.02624***	0.0758	0.003455	0.0007346	0.004189
	[0.1312]	[0.002967]	[0.02153]	[0.02286]	[0.04949]	[0.002207]	[0.0005446]	[0.002654]
High Technology Exports	0.1749***	0.003582***	0.0123***	0.01588***	0.07558***	0.003454***	0.0008048***	0.004259***
	[0.07842]	[0.001706]	[0.0142]	[0.01511]	[0.02948]	[0.001232]	[0.0004592]	[0.001588]
ISO14001	1.035***	0.02043***	0.06057***	0.081***	0.3712***	0.01716***	0.003824***	0.02098***
	[0.3974]	[0.007039]	[0.05366]	[0.05447]	[0.07466]	[0.003184]	[0.001392]	[0.003627]
Manufacture Tariff	-0.1354	-0.002557	-0.003205	-0.005762	-0.04607	-0.00216	-0.0004	-0.00256
	[0.2325]	[0.004774]	[0.01373]	[0.01738]	[0.06577]	[0.003118]	[0.00069]	[0.0037]
Spatial lag	0.7035***				0.189***			
	[0.1286]				[0.0625]			
Observations	141							
Total Draws / Omitted Draws	15000 /1000							
Thinning Factor	10							
I-statistic	1.991							
Log-likelihood	-14.033							
Pseudo R²	0.844							

Note: The mean of the posterior distribution is reported as coefficient while the standard deviation is reported in the brackets.
*** significant at 1%, ** significant at 5%, * significant at 10%.

Table 6: Spatial Weight Robustness Check Results (continued)

	Spatial Probit with Trade Intensity				Spatial Probit with Structural Equivalence			
Variable	Coefficient	Direct Effect	Indirect Effect	Total Effect	Coefficient	Direct Effect	Indirect Effect	Total Effect
Constant	-1.521				1.657			
	[7.263]				[7.402]			
Real GDP per Capita	0.2034***	0.006572***	0.0008482*	0.007421***	0.2297***	0.007915***	0.003807*	0.01172***
	[0.09104]	[0.003072]	[0.001067]	[0.003583]	[0.09484]	[0.003213]	[0.003975]	[0.006113]
So2	-0.06243	-0.001975	-0.0002736	-0.002248	-0.05436	-0.00185	-0.0008822	-0.002732
	[0.04674]	[0.001459]	[0.0004408]	[0.001707]	[0.04434]	[0.001483]	[0.001283]	[0.002468]
Political & Civil Rights	-0.6822*	-0.02235*	-0.003476	-0.02582*	-0.4082	-0.01441	-0.006713	-0.02112
	[0.4443]	[0.01477]	[0.005609]	[0.01838]	[0.3318]	[0.012]	[0.0091]	[0.01897]
Population Below 45	-0.2602**	-0.008447**	-0.001202	-0.009649**	-0.2461*	-0.008514*	-0.00431	-0.01282*
	[0.139]	[0.004627]	[0.001807]	[0.005687]	[0.1435]	[0.004985]	[0.005308]	[0.009128]
Environmental Treaties	0.1812***	0.005828***	0.0008063*	0.006634***	0.1403***	0.004797***	0.002161*	0.006958***
	[0.05639]	[0.001654]	[0.0009631]	[0.002231]	[0.04656]	[0.001366]	[0.001882]	[0.002501]
Manufacture Value Added	0.1712**	0.005335**	0.0008922	0.006228**	0.1372*	0.00474*	0.002353	0.007093*
	[0.1074]	[0.003035]	[0.001461]	[0.004106]	[0.07633]	[0.002662]	[0.002784]	[0.004757]
High Technology Exports	0.09586**	0.003074**	0.0004225	0.003497**	0.0919**	0.003142**	0.00144*	0.004583**
	[0.05225]	[0.001653]	[0.0005956]	[0.002002]	[0.04822]	[0.001582]	[0.001477]	[0.002598]
ISO14001	0.497***	0.0166***	0.001596*	0.01819***	0.4183***	0.01443***	0.005689*	0.02012***
	[0.16]	[0.006774]	[0.001146]	[0.00654]	[0.1349]	[0.004717]	[0.003825]	[0.005265]
Manufacture Tariff	-0.2818*	-0.009107*	-0.001338	-0.01045*	-0.1691	-0.005856	-0.002642	-0.008498
	[0.1744]	[0.005612]	[0.002198]	[0.006909]	[0.1148]	[0.004125]	[0.003425]	[0.006487]
Spatial lag	0.1047*				0.2808*			
	[0.09167]				[0.1546]			
Observations	141				141			
Total Draws / Omitted Draws	15000 /1000				15000 /1000			
Thinning Factor	7				6			
I-statistic	1.787				1.628			
Log-likelihood	-34.690				-28.111			
Pseudo R^2	0.613				0.687			

Note: The mean of the posterior distribution is reported as coefficient while the standard deviation is reported in the brackets.
*** significant at 1%, ** significant at 5%, * significant at 10%.

Results given in Table 6 are qualitatively similar in terms of direct effect independently of the spatial weight considered. This is additional evidence of the robustness of the benchmark results. The differences in the marginal indirect effects (and thus total effects) are mainly due to the average value taken by the posterior distribution of the spatial autoregressive parameter. For instance, the spatial lag associated with the inverse geographical distance weight matrix is larger than any other spatial scheme. This suggests that spatial interactions in the eco-label decision are not bounded within their own geographical region. For instance, the Japanese government will not only consider the actions of its Asian neighbors, but also pay attention to European nations as well as the United States. This is partially confirmed when the spatial lag is based on structural export equivalence. As one expected, strategic dependence goes beyond pure geographical and political distances and can include trade competition among structural equivalent economies. In other words, two countries close geographically and trading intensively but whose manufacturing industries are structurally different will not share a strong strategic interaction in the decision to implement an eco-labelling scheme (e.g. one country trades food goods, while the other one trades manufacturing goods). This could partially explain why the spatial autoregressive is relatively small with trade intensity. The other reason might be due the fact that the spatial weight matrix with bilateral trade is no longer strictly exogenous (but potentially predetermined). Yet the main findings remain almost unchanged, except that the substitutive relationship between the average manufacturing tariff and the decision to introduce an eco-label is now statistically significant. This is in line with the view that eco-label might promote non-trade tariff barriers. But since this finding is not robust, this suggests that the underlying protectionist motivation behind the implementation of an eco-labelling scheme is not as strong as least developed countries might fear.

6.3 Spatial Error and Durbin Models

Due to data availability, it is extremely difficult to consider other potential explanatory variables without reducing drastically the sample size[19]. By reducing the number of countries, not only is the notion of interdependence altered, but the MCMC algorithm will yield less efficient estimates. That is why, I restrict myself to estimate an extended version of the benchmark model, known as the spatial Durbin model, to account for potential additional spatial variables omission.

[19] Several other specifications were estimated that included GDP per capita squared, European Union dummy, ... Although those results lead to the same conclusion, they suffer from high collinearity and lack of converge in the MCMC estimation. Other explantory variables, like innovation index or corruption index could not have been included as they cover a limited number of countries.

Beside the spatial lag, spatial dependence can also be specified in the error term. The spatial error model whose errors are spatially correlated reads as:

$$\begin{aligned}
\mathbf{Y}^{\star} &= \mathbf{X}\beta + \mathbf{e} \\
\mathbf{e} &= \lambda\mathbf{W}\mathbf{e} + \mathbf{u}
\end{aligned}$$

Estimation of the spatially autocorrelated error model through the MCMC method is very similar to the spatial lag model, because the prior of each parameter is defined independently of each other. The marginal effects in a spatial error model are computed as follows:

$$\widehat{\Xi}_{ijr} = \phi\left(\left[X\widehat{\beta}\right]_i / \widehat{t}_i\right)\widehat{\beta}_r / \widehat{t}_i$$

where $\widehat{t}_i = \widehat{\sigma}^2 \sum_i \widehat{\omega}_{ij}^2$ with ω_{ij} being the ij^{th} elements of the matrix $(I - \lambda\mathbf{W})^{-1}\,\mathbf{u}$.

Ignoring spatial error dependence yields an omitted variable bias, when the omitted variables are spatially dependent. The issue is that the spatial lag might capture uncorrected spatial dependence related to the error term. Despite its econometric foundation, there is no direct economic interpretation of the expected sign of the spatial error term. As highlighted by Pace and LeSage (2007), the spatial Durbin model has the advantage of reducing spatially dependent omitted variable bias and having a direct economic interpretation. The spatial Durbin model corresponds to the extension of the benchmark model which includes the spatially weighted average of the dependent variable ($\mathbf{W}\mathbf{Y}^{*}$) as well as the explanatory variables beside the constant term ($\mathbf{W}\mathbf{X}^{nc}$):

$$\mathbf{Y}^{\star} = \rho\mathbf{W}\mathbf{Y}^{\star} + \mathbf{X}\beta + W\mathbf{X}^{nc}\boldsymbol{\gamma} + \mathbf{u}$$

Note that in the spatial Durbin model, the spatial effects are modified to account for the presence of the spatial covariates:.

$$\begin{aligned}
\widehat{\Xi}_{ijr} &= \phi\left(\left[(I_N - \widehat{\rho}\mathbf{W})^{-1}\left(X\widehat{\beta} + W\mathbf{X}^{nc}\widehat{\boldsymbol{\gamma}}\right)\right]_i / \widehat{s}_i\right) \cdot \\
&\quad \left(\left[(I_N - \widehat{\rho}\mathbf{W})^{-1}\right]_{ij}\widehat{\beta}_r + \left[(I_N - \widehat{\rho}\mathbf{W})^{-1}\,\mathbf{W}\right]_{ij}\widehat{\gamma}_r\right) / \widehat{s}_i
\end{aligned}$$

One important drawback of the spatial Durbin model is the introduction of additional collinearity as it is the case here. As a consequence, there are some convergence issues. That is why, some of the MCMC settings are modified. In particular, the number of burn-in and draws are set to $20,000$ and $80,000$, respectively, because the posterior distribution of the spatial lag is not converging with a smaller number of draws.

Table 7: Spatial Error and Durbin Results

Variable	Spatial Error Probit: Coefficient	Spatial Error Probit: Marg. Effect	Spatial Durbin Probit with Exponential Distance: Coefficient (x)	Spatial Coefficient (wx)	Direct Effect	Indirect Effect	Total Effect
Constant	6.001		-0.468				
	[7.965]		[9.3]				
Real GDP per Capita	0.812***	1.429***	0.7615***	-0.4096	0.003765***	-0.002572	0.001194
	[0.37]	[0.6397]	[0.2956]	[0.555]	[0.002885]	[0.002955]	[0.002576]
So2	-0.1228	-0.2126	-0.4487***	-1.326***	-0.001859**	-0.00407***	-0.005929***
	[0.09269]	[0.1808]	[0.1768]	[0.3282]	[0.001481]	[0.002995]	[0.004058]
Political & Civil Rights	0.4085	0.969	4.309***	-15.61***	0.02416***	-0.0614***	-0.03724***
	[0.7737]	[1.746]	[1.716]	[4.801]	[0.01809]	[0.0441]	[0.02988]
Population Below 45	-0.7465**	-1.289**	-0.2454	-0.5519	-0.001129	-0.001403	-0.002532
	[0.3745]	[0.6424]	[0.4707]	[1.018]	[0.00267]	[0.004261]	[0.004569]
Environmental Treaties	0.4159***	0.7319***	0.5155***	1.435***	0.002103**	0.004344***	0.006446***
	[0.1668]	[0.2558]	[0.1815]	[0.439]	[0.00164]	[0.003252]	[0.004531]
Manufacture Value Added	0.3914**	0.6839**	0.9894***	2.202**	0.00416**	0.00648**	0.01064***
	[0.2103]	[0.3663]	[0.3351]	[0.8234]	[0.003233]	[0.005563]	[0.007539]
High Technology Exports	0.1622	0.2791	0.4167***	1.387**	0.001663**	0.004346*	0.006009***
	[0.1033]	[0.1859]	[0.1412]	[0.6294]	[0.001338]	[0.003935]	[0.004533]
ISO14001	0.8595***	1.51***	1.415***	0.07123	0.006748***	-0.001922**	0.004825***
	[0.3398]	[0.5316]	[0.2654]	[0.4511]	[0.004502]	[0.001568]	[0.003604]
Manufacture Tariff	0.03701	0.09095	1.269***	-2.431	0.006729***	-0.01045*	-0.003724
	[0.1758]	[0.3886]	[0.3384]	[1.477]	[0.004734]	[0.009073]	[0.005871]
Spatial error	0.9505***						
	[0.03872]						
Spatial lag			-0.4117**				
			[0.1727]				
Observations			141				
Total Draws / Omitted Draws			80000 /20000				
Thinning Factor			5				
I-statistic			1.156				
Log-likelihood			-0.312				
Pseudo R²			0.997				

Note: The mean is reported as coefficient while,the standard deviation is reported in the brackets.
*** significant at 1%, ** significant at 5%, * significant at 10%.

Table 7 reports the results of the spatial error and Durbin probit models with the negative exponential distance weighting scheme. In comparison with the spatial autoregressive model, the spatially autocorrelated error model yields higher posterior mean for each parameter, including the spatial error variable $\left(\widehat{\lambda} = 0.95\right)$. As a consequence, the marginal effects are larger than the direct effects in the benchmark model. Since the errors seems to be spatially correlated, it might be justified to consider the spatial Durbin model to control for the potential omitted variable bias in the spatial error. As mentioned previously, the spatial Durbin model suffers from multicollinearity, which explains why the posterior mean of most variables is higher (in particular the political and civil liberties index). Most spatial covariates, which are statistically significant, implies positive externalities on the decision to introduce an eco-label. In other words, the average government will not only look if its partners have implemented an eco-labelling scheme, but also consider their economic characteristics. As a consequence, these positive spillovers stemming from neighborhood characteristics lead to higher indirect marginal effects in absolute value for most explanatory variables. Finally, accounting for spatial dependence in the error term yields a negative and significant spatial autoregressive coefficient. The results suggest now that the average country behaves as a leader and implement an eco-labelling scheme if its partners don't have or don't plan on introducing one.

7 Conclusion

The decision of a government to introduce an eco-labelling scheme program depends on many factors. One potential determinant, usually omitted in empirical literature, is the existence of interdependence in the adoption's decision. To address this issue, a limited dependent variable spatial probit model is estimated through a Markov Chain Monte Carlo method using a joint update sampler algorithm. In comparison with an aspatial specification, accounting for the spatial dependence leads to a higher explanatory power of the model. The main findings indicate that the probability for a government to introduce an eco-labelling scheme is positively related to the economy's stage of development decision, the existence of potential scale effects as well as a relative production cost advantage through innovation. In addition, there is robust evidence that suggests that the eco-label adoption is a strategic decision with respect to other countries' decision. Obviously, in order to reach a definitive conclusion about the view that eco-label might be used as non-tariff trade barrier, one should be able to demonstrate that the eco-label has lead to a decrease in the imports level of the same type of good. Unfortunately, the lack of information makes it difficult to empirically highlight this mechanism.

Nevertheless, the empirical evidence provided here suggests that in order for an eco-label program to be as transparent and unbiased as possible and thus avoid any trade barrier effects, harmonization in the standards, greater transparency in the certification awarding and mutual recognition in eco-labelling schemes are needed. Obviously, these changes cannot be achieved so easily. Mainly because it does not only involve national governments but also the implicated industries and agencies in both developed and developing countries.

Future research should account for the time dynamic in the eco-label program implementation and thus consider a dynamic extension of the spatial probit model for several reasons. First, the starting phase of most eco-labelling schemes is associated with procedural and methodological uncertainties that could be even more important and lasting in developing countries. Second, most current eco-labels in developed countries are able to exist because of subsidies. A slowed economy or a change in environmental policy could limit the sources of subsidies (e.g. individual supports, foundations, governments) affecting the functioning of eco-label programs. Third, the important consolidation and vertical integration within and between most segments of the market chains, that have been taken place during the past 30 years, can also alter the industry market structure and affect the eco-labelling schemes. Last but not least, the potential oversupply of eco-labels may prevent consumption of environmentally friendly products because of information congestion. This could ultimately lead to the elimination of some eco-labelling schemes that cannot face competition among other eco-labels. Hopefully, with the development of better disaggregated data on eco-labelled trade flows, additional investigation will help to disentangle the different effects that are at play between eco-labels and international trade.

8 Appendices

8.A Relative Algorithms Performance

Performance relative to Joint Update with Metropolis-Hastings

	Iterative Update with Geweke & Metropolis-Hastings		Iterative Update with Rodriguez-Yam et al. & Metropolis-Hastings	
Observations	Dependence Factor	Param. Distance	Dependence Factor	Param. Distance
250	1.102	0.659	1.168	0.935
500	1.287	0.724	1.378	0.974
750	1.397	0.797	1.387	1.031
1000	1.569	0.869	1.454	1.124

Performance relative to Joint Update with numerical integration

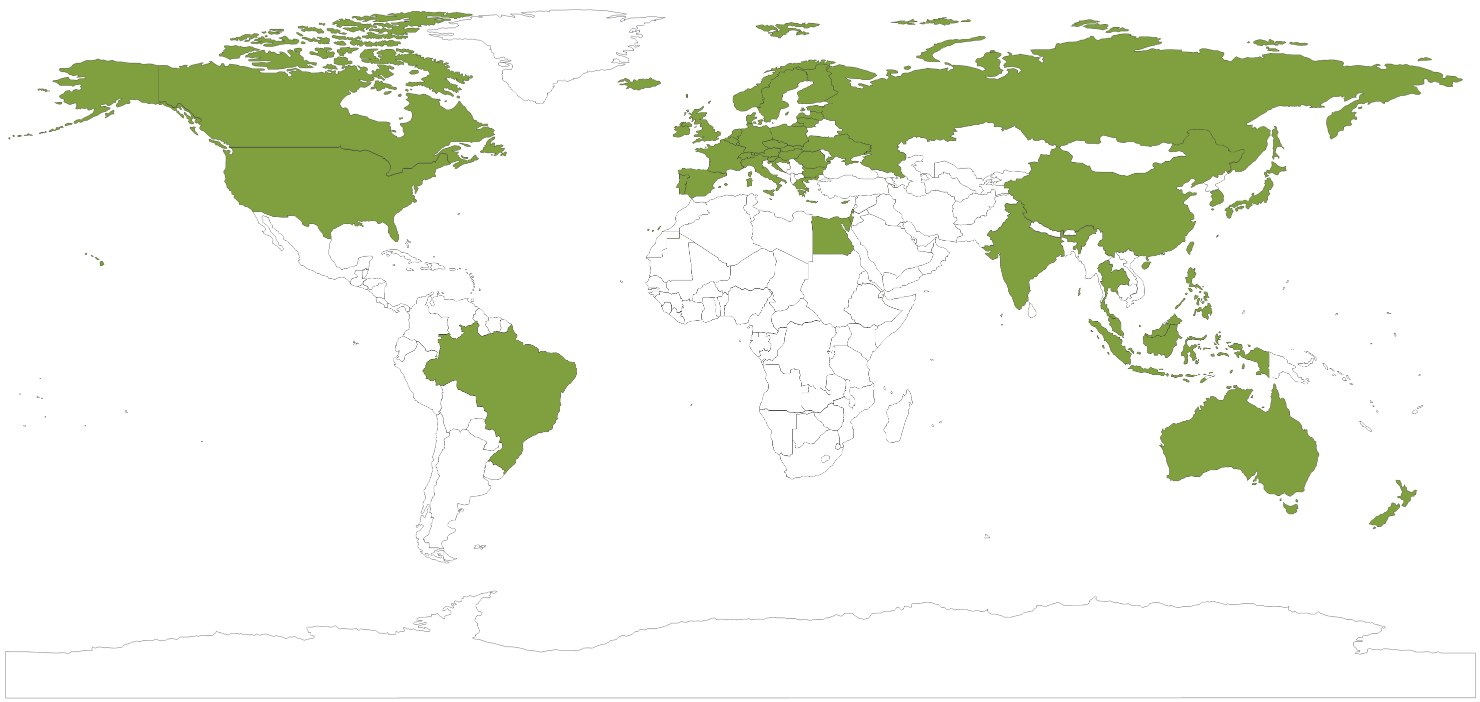
	Iterative Update with Geweke & Numerical Integration		Iterative Update with Rodriguez-Yam et al. & Numerical Integration	
Observations	Dependence Factor	Param. Distance	Dependence Factor	Param. Distance
250	1.256	0.684	1.234	0.950
500	1.274	0.745	1.233	0.976
750	1.455	0.818	1.276	1.022
1000	1.469	0.879	1.290	1.064

8.B Manufactured Multi-products Eco-Label List

Country	National Eco-label	Supranational Eco-label		Country	National Eco-label	Supranational Eco-label
Australia	1991			Korea, Rep.	1992	
Austria	1990	1992‡		Latvia		2004‡
Belgium		1992‡		Liechtenstein		1992‡
Brazil	1992			Lithuania	2001	2004‡
Bulgaria		2007‡		Luxembourg	1992	1992‡
Canada	1988			Malaysia	1996	
China	1993			Malta		2004‡
Croatia	1993			Netherlands	1992	1992‡
Cyprus		2004‡		New Zealand	1990	
Czech Republic	1993	2004‡		Norway		1989†, 1992‡
Denmark		1989†, 1992‡		Philippines	2001	
Egypt, Arab Rep.	1999			Poland	2004	2004‡
Estonia		2004‡		Portugal		1992‡
Finland		1989†, 1992‡		Romania		2007‡
France	1992	1992‡		Russian Federation	2007	
Germany	1977	1992‡		Singapore	1992	
Greece		1992‡		Slovak Republic	1996	1996‡
Hong Kong, China	2000			Slovenia		2004‡
Hungary	1994	1994‡		Spain	1994	1992‡
Iceland		1989†, 1992‡		Sweden	1989	1989†, 1992‡
India	1991			Switzerland	2000	
Indonesia	1994			Taiwan	1992	
Ireland		1992‡		Thailand	1994	
Israel	1993			Ukraine	2002	
Italy		1992‡		United Kingdom		1992‡
Japan	1989			United States	1988	

Note: † Nordic Swan; ‡ EU Eco-labelling

8.C Manufactured Multi-products Eco-Label Map of the World



8.D Country List

Albania
Algeria
Angola
Argentina
Armenia
Australia
Austria
Azerbaijan
Bangladesh
Belarus
Belgium-Luxembourg
Belize
Benin
Bolivia
Bosnia and Herzegovina
Botswana
Brazil
Bulgaria
Burkina Faso
Burundi
Cambodia
Cameroon
Canada
Central African Republic
Chad
Chile
China
Colombia
Congo, Dem. Rep.
Congo, Rep.
Costa Rica
Croatia
Cyprus
Czech Republic
Côte d'Ivoire
Denmark
Djibouti
Dominican Republic
Ecuador
Egypt, Arab Rep.
El Salvador
Estonia
Ethiopia
Finland
France
Gabon
Georgia
Germany
Ghana
Greece
Guatemala
Guinea
Guinea-Bissau
Guyana
Honduras
Hong Kong, China
Hungary
Iceland
India
Indonesia
Iran, Islamic Rep.
Ireland
Israel
Italy
Jamaica
Japan
Jordan
Kazakhstan
Kenya
Korea, Rep.
Kuwait
Kyrgyz Republic
Lao PDR
Latvia
Lebanon
Lithuania
Macedonia, FYR
Madagascar
Malawi
Malaysia
Mali
Mauritania
Mauritius
Mexico
Moldova
Mongolia
Morocco
Mozambique
Namibia
Nepal
Netherlands
New Zealand
Nicaragua
Niger
Nigeria
Norway
Oman
Pakistan
Panama
Papua New Guinea
Paraguay
Peru
Philippines
Poland
Portugal
Romania
Russian Federation
Rwanda
Saudi Arabia
Senegal
Sierra Leone
Slovak Republic
Slovenia
South Africa
Spain
Sri Lanka
Sudan
Swaziland
Sweden
Switzerland
Syrian Arab Republic
Tajikistan
Tanzania
Thailand
Togo
Trinidad and Tobago
Tunisia
Turkey
Turkmenistan
Uganda
Ukraine
United Arab Emirates
United Kingdom
United States
Uruguay
Uzbekistan
Venezuela, RB
Vietnam
Yemen, Rep.
Zambia
Zimbabwe

8.E Data Sources

Factors	Variable	Expected sign	Source
Stage of development	Real GDP Per Capita	+	WDI 2007
Economic Efficiency	Civil And Political Liberties Index	+	Freedom House
Pollution Pressure	SO2 Emission level	+	EDGAR
Scale Effect	Manufacture Value Added	+	WDI 2007
Price Premium	Population Below 45 Years Old	+	U.S. Census Bureau
Environmental Experience	International Environmental Treaties	+	ENTRI
Innovation	High Technology Exports	+	WDI 2007
Innovation	ISO14001 Certificates	+	ISO
Non-Tariff Barriers	Manufacturing Tariffs	-/+	WDI 2007
Spatial Dependence	Geographical Distance	-/+	CEPII
Spatial Dependence	Political Distance	-/+	Gleditsch Ward (2001)
Spatial Dependence	Bilateral Trade Flows/Structural Equivalence	-/+	UN Comtrade

Note: Non spatial data is averaged over 2003-2005, except SO2 emission data only available for 2000.

8.F Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max	Moran I
Eco-label	141	0.33	0.47	0	1	0.57***
Real GDP per capita	141	8967.93	13800.01	38.76	62812.54	0.54***
So2 emissions	141	91.78	13.29	0	99.8	0.2***
Political and civil liberties	141	-3.37	1.85	-7	-1	0.48***
Population share below 45 years old	141	41.09	4.88	31.17	65.05	0.48***
Environmental treaties	141	41.35	20.45	4	104	0.68***
Manufacture value-added	141	15.19	7.57	2.3	42	0.34***
High-technology exports	141	0.09	0.12	0	0.71	0.16***
ISO14001 certificates	141	775.67	2565.73	0	21881	0.26***
Manufacture tariff	141	8.63	5.57	0	31.85	0.44***

Note: The Moran statistics tests the absence of spatial autocorrelation.

*,** and *** denotes significance at 10%, 5% and 1%, respectively.

8.G Correlation Matrix

	Eco-label	real GDP per capita	So2 emission	Political liberties	Population below 45	Env. Treaties	Manuf. value added	Technology exports	ISO certificates	Manuf. tariff
Eco-label	1									
Real GDP per capita	0.65***	1								
So2 emission	-0.43***	-0.42***	1							
Political and civil liberties	0.58***	0.55***	-0.32***	1						
Population share below 45 years old	0.42***	0.4***	-0.46***	0.27***	1					
Environmental treaties	0.71***	0.64***	-0.37***	0.62***	0.37***	1				
Manufacture value-added	0.44***	0.13	-0.16*	0.21**	0.39***	0.35***	1			
High-technology exports	0.48***	0.33***	-0.22***	0.31***	0.23***	0.25***	0.28***	1		
ISO14001 certificates	0.4***	0.34***	-0.21**	0.19**	0.18**	0.35***	0.26***	0.26***	1	
Manufacture tariff	-0.53***	-0.56***	0.33***	-0.57***	-0.45***	-0.51***	-0.3***	-0.3***	-0.21**	1

Note: *,** and *** denotes significance at 10%, 5% and 1%, respectively.

References

[1] Albert, J. H., & S. Chib, 1993. "Bayesian Analysis of Binary and Polychotomous Response Data", Journal of the American Statistical Association, 88, pp. 669-679.

[2] Basu, A. K., Chau, N. H. & U. Grote, 2004. "On Export Rivalry and the Greening of Agriculture – the Role of Eco-labels," Agricultural Economics, 31(2-3), pp. 135-147.

[3] Beaulieu, E. & J. Gaisford, 2002. "Labour and Environmental Standards: The 'Lemons Problem' in International Trade Policy," The World Economy, 25(1), pp. 59-78.

[4] Beron, K. J., Murdoch, J. C. & W. P. M. Vijverberg, 2003. "Why Cooperate? Public Goods, Economic Power, and the Montreal Protocol," The Review of Economics and Statistics, 85(2), pp. 286-297.

[5] Bonsi, R. Hammett, A.L., & B. Smith, 2008. "Eco-labels and International Trade: Problems and Solutions", Journal of World Trade, 42(3), pp. 407-432.

[6] Bruce, C., & A. Laroiya, 2007. "The Production of Eco-Labels," Environmental and Resource Economics, 36(3), pp. 275-293.

[7] Cao, X. & A. Prakash, 2009, "Trade Competition and Domestic Pollution: A Panel Study, 1980-2003," International Organization, forthcoming.

[8] Cole, M. A., Elliott, R. J. R., & K. Shimamoto, 2005. "Industrial Characteristics, Environmental Regulations and Air Pollution: an Analysis of the UK Manufacturing Sector," Journal of Environmental Economics and Management, 50(1), pp. 121-143.

[9] Fleming, M., 2002. "Techniques for Estimating Spatially Dependent Discrete Choice Models," in Anselin, L., Florax, R. J., and Rey, S. J., editors, Advances in Spatial Econometrics. Springer-Verlag, Heidelberg.

[10] Franzese, R. J., & J. C. Hays, 2008. "The Spatial Probit Model of Interdependent Binary Outcomes: Estimation, Interpretation and Presentation".

[11] Galarraga, I. G., 2002. "The Use of Eco-labels: a Review of the Literature." European Environment, 12(6), pp. 316-331.

[12] Geweke, J, 1993. "Bayesian Treatment of the Independent Student-t Linear Model," Journal of Applied Econometrics, 8, pp. 19-40.

[13] Greaker, M., 2006. "Eco-labels, Trade and Protectionism," Environmental and Resource Economics,33, pp. 1-37.

[14] Grolleau, G. & S. El Harbi, 2008. "Why some Countries Adopt Ecolabeling Schemes in their Regulatory Arsenal and Others Do Not?," Economics Bulletin, Economics Bulletin, 17(3), pp. 1-11.

[15] Holloway, G., Bhavani, S., & R. Sanzidur, 2002. "Bayesian spatial probit estimation: a primer and an application to HYV rice adoption," Agricultural Economics, 27(3), pp383-402.

[16] Holmes C. C. & L. Held, 2006. "Bayesian Auxiliary Variable Models for Binary and Multinomial Regression.", Bayesian Analysis, 1(1), pp. 145-168.

[17] Kern, K., Jörgens, H., & M. Jänicke, 2001. "The Diffusion of Environmental Policy Innovations. A Contribution to the Globalisation of Environmental Policy," Discussion Paper FS II 01-302. Social Science Research Centre: Berlin.

[18] LeSage, J.P., 2000. "Bayesian Estimation of Limited Dependent Variable Spatial Autoregressive Models," Geographical Analysis, 32, pp. 19-35.

[19] LeSage, J.P. & O. Parent, 2007. "Bayesian Model Averaging for Spatial Econometric Models.", Geographical Analysis, 39(3), pp. 241-267.

[20] LeSage, J. & R. K. Pace, 2009, "Introduction to Spatial Econometrics," CRC Press Inc.

[21] Magnani, E., 2000. "The Environmental Kuznets Curve, Environmental Protection Policy and Income Distribution," Ecological Economics, 32(3), pp. 431-443.

[22] McMillen, D.P., 1992. "Probit with Spatial Autocorrelation," Journal of Regional Science, 3, pp. 335-348.

[23] Mattoo, A. and H.V. Singh, 1994. "Eco-labelling: Policy Considerations,", Kyklos 47(1), pp. 53-65.

[24] Melser, D., & P. E. Robertson, 2005. "Eco-labelling and the Trade-Environment Debate," The World Economy, 28(1), pp. 49-62.

[25] Nadai, A., 1999. "Conditions for the Development of a Product Ecolabel," European Environment, 9, pp. 202-211.

[26] OCDE, 2004. "Effects of Eco-labelling Schemes: Compilation of Recent Studies," Joint Working Party on Trade and Environment.

[27] Piotrowski, R. & S. Kratz, 1999, "Eco-labelling in the Globalised Economy", International Politics and Society, 4, pp. 430-443.

[28] Peattie, K., 2001. "Golden Goose or Wild Goose? The Hunt for the Green Consumer," Business Strategy and the Environment, 10, pp. 187-199.

[29] Pedersen, E.R. & P. Neergaard, 2006, "Caveat Emptor – Let the Buyer Beware! Environmental Labelling and the Limitations of 'Green' Consumerism.", Business Strategy and the Environment, 15(1), pp. 15-29.

[30] Pinkse, J. & M. Slade, 1998. "Contracting in Space: An Application of Spatial Statistics to Discrete Choice Models," Journal of Econometrics, 85, pp. 125-154.

[31] Porter, M. E & C. van der Linde, 1995. "Toward a New Conception of the Environment-Competitiveness Relationship," Journal of Economic Perspectives, 9(4), pp. 97-118.

[32] Raftery, A.E. & S.M. Lewis, 1992. "One Long Run with Diagnostics: Implementation Strategies for Markov Chain Monte Carlo," Statistical Science, 7, pp. 493-497.

[33] Raftery, A.E. & S.M. Lewis, 1995. "The Number of Iterations, Convergence Diagnostics and Generic Metropolis Algorithms," in Practical Markov Chain Monte Carlo, W.R. Gilks, D.J. Spiegelhalter & S. Richardson, eds..

[34] Rodriguez-Yam, G., Davis, R. A., & L. Scharf, 2004. "Efficient Gibbs Sampling of Truncated Multivariate Normal with Application to Constrained Linear Regression."

[35] Sammer, K., & R. Wüstenhagen, 2006. "The Influence of Eco-Labelling on Consumer Behaviour - Results of a Discrete Choice Analysis for Washing Machines," Business Strategy and the Environment, 15, pp. 185-199.

[36] Sedjo, R. A., & S. K. Swallow, 2002. "Voluntary Eco-Labeling and the Price Premium," Land Economics, 78(2), pp. 272-284.

[37] Smith, T. E. & J. P. LeSage, 2004. "A Bayesian Probit Model with Spatial Dependencies," in Advances in Econometrics: Volume 18: Spatial and Spatiotemporal Econometrics, J. P. LeSage & R. K. Pace (eds.), Oxford, pp. 127-160.

[38] Swallow, S.K. and R.A. Sedjo, 2000. "Eco-labeling Consequences in General Equilibrium: A Graphical Assessment," Land Economics 76(2), pp. 28-36.

[39] Teisl, M. F., Roe, B., & A. S. Levy, 1999. "Ecocertification: Why It May Not Be a Field of Dreams," American Journal of Agricultural Economics, 81(5), pp. 1066-1071.

[40] Thomas, T.S., 2007. "A Primer for Bayesian Spatial Probits with an Application to Deforestation in Madagascar."

[41] UNEP, 2005. "The Trade and Environmental Effects of Ecolabels: Assessment and Response."